UNIVERSITY OF SOUTHAMPTON

FACULTY OF ENGINEERING AND THE ENVIRONMENT

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Using AIS data to calculate emissions inventories for small commercial watercraft

by

Jonathan Coello

Thesis for the degree of Doctor of Philosophy

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ABSTRACT

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The shipping industry is heavily reliant on the use of fossil fuel and contributes significantly to global emissions of carbon dioxide (CO_2), nitrogen oxides (NO_x), sulphur dioxide (SO_2) and particulate matter (PM) resulting in deleterious impacts upon the climate, human health and the environment. A large proportion of global fishing and other small commercial vessels (< 100 GT) are omitted from global shipping emissions inventories, leading to potentially significant underestimation of emissions from the shipping sector. Effective quantification of shipping emissions requires quality data and sophisticated methods. This thesis introduces a new method for the calculation of emissions inventories for small commercial vessels that utilises Automatic Identification System (AIS) data, a high-quality source of activity data for modelling atmospheric emissions from ships. The methodology offers a novel approach to activity sampling for modelling the emissions of vessels that cannot be directly matched to AIS data. A new speed calculation methodology based on the AIS data is also developed. An approach is also introduced for the detection of pushing and towing operations of vessels such as dredgers and trawlers in order that corrected engine load estimates can be applied for these operations. A case study emissions inventory for the year from May 2012 to May 2013 is calculated for UK fishing vessels. This is compared with the annual emissions calculated using a fuel-based methodology. Fuel use calculated using the activity-based methodology is 270.8 kt, which is slightly higher than the fuel-based methodology which yielded results of 251.8 kt. The activity-based method produced a CO_2 emissions estimate of 864.3 kt, compared to 803.3 kt for the fuel-based approach. An analysis of uncertainty and sensitivity shows that activity sampling and emission factor uncertainty produce significant but unbiased uncertainty in results. However, uncertainties in values used to parameterise engine load calculation are found to generate potentially significant bias in results, highlighting the importance of calibrating model input parameters to ensure that sensible results are produced. Overall uncertainties in fuel use and emissions calculated using the activity-based method are found not to exceed ±6% at the 95% confidence interval. The close alignment of the results of the fuel-based and activity-based methods and the relative stability of results shown by the uncertainty analysis indicates that an AIS-based methodology with activity sampling is a viable approach for the calculation of emissions from small commercial vessels. The finding that 43.5% of UK fishing fleet emissions are produced by small vessels (< 100 GT) supports the claim that omitting these vessels from emissions inventories could lead to a significant underestimation of shipping emissions.

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Definitions and abbreviations

AIS	Automatic identification systems
AMSA	Arctic Maritime Shipping Assessment
AMVER	Automated Mutual-Assistance Vessel Rescue System
CO	Carbon monoxide
CO_2	Carbon dioxide
CO_2e	Carbon dioxide equivalent
COADS	Comprehensive Ocean-Atmosphere Data Set
DECC	Department of Energy and Climate Change
D_{max}	Maximum possible time between AIS data points sharing the same timestamp
DOAS	Differential Absorption Spectrometry
ECCFFR	European Commission Community Fishing Fleet Register
EEA	European Environment Agency
EC	European Commission
EF	Emission factor
EIA	Energy Information Administration
EMEP	European Monitoring and Evaluation Programme
EU	European Union
FOA	Food and Agricultural Organization
GHG	Greenhouse gas
GIS	Geographic Information Systems
GT	Gross tonnage
GPS	Global Positioning System
IEA	International Energy Agency
IPCC	Intergovernmental Panel on Climate Change
IMO	International Maritime Organization
LF	Load factor
LHS	Latin hypercube sampling
LMIU	Lloyds Marine Intelligence Unit
MCA	Maritime Coastguard Agency
MCR	Maximum continuous rating
MMO	Marine Maritime Organization

MMSI	Marine Mobile Service Identity
NCAR	National Centre for Atmospheric Research
NMVOC	Non-methane volatile organic compound
NOAA	National Oceanic and Atmosphere Administration
NO_x	Nitrogen oxides
NTUA	National Technical University of Athens
N_2O	Nitrous oxide
OAT	One-at-a-time (sensitivity analysis)
P	Engine power
PM	Particulate matter
RAM	Random-access memory
RoI	Republic of Ireland
SFC	Specific fuel consumption
SFOC	Specific fuel oil consumption
SOG	Speed over ground
SOLAS	Safety of Life At Sea
SO_2	Sulphur dioxide
STEAM	Ship Traffic Emission Assessment Model
STW	Speed through water
T	Engine running time
UNFCCC	United Nations Framework Convention on Climate Change
UTC	Coordinated Universal Time
UK	United Kingdom
V_i	Instantaneous vessel speed
V_d	Vessel design speed
VHF	Very high frequency
VOC	Volatile organic compound

Terminology

AIS data point	The information contained within an AIS position update message.
AIS track	The set of AIS data points identified by a particular MMSI number sorted in chronological order, with information calculated for track segments.
Track segment	The vessel activity between two chronologically consecutive AIS data points in an AIS track. Track segments have a duration, speed and relative speed.
Minimum moving speed	The speed threshold above which a vessel is classified as moving.
Instantaneous speed	The average speed of a vessel during a specific track segment.
Design speed	The maximum speed that a vessel is designed to cruise at.
Maximum speed	A maximum speed derived from an AIS track that is used as a proxy for design speed when design speed is unavailable from vessel characteristic data.
Relative speed	The ratio of instantaneous speed to design speed
Moving track segment	A track segment where the instantaneous speed is greater than or equal to the minimum moving speed.
Moving (%)	The percentage (by duration) of an AIS track or group of AIS tracks made up of moving track segments.
Mean speed	The mean speed of all track segments of an AIS track or group of AIS tracks.
Mean moving speed	The mean speed of all moving track segments of an AIS track or group of AIS tracks.
Mean relative speed	The mean relative speed of all track segments of an AIS track or group of AIS tracks.
Mean moving relative speed	The mean relative speed of all moving track segments of an AIS track or group of AIS tracks.
Mean max speed	The mean maximum speed of a group of AIS tracks

A note on units

Within this thesis speed is presented in either knots or km h^{-1}. It is acknowledged that km h^{-1} is not an SI unit. For the reader's convenience, conversion formulae are provided:

- 1 km h^{-1} = 0.54 knots,
- 1 km h^{-1} = 0.28 ms^{-1}

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Accompanying materials

A folder of digital materials are provided in accompaniment to this thesis, which contains:

- The source code of the software developed during this project [ShipEmissionsModel directory].
- Software documentation [ShipEmissionsModelDocumentation.pdf].
- The input data used in the production of the case study emissions inventory [CaseStudyData directory], including:
    - AIS data,
    - vessel characteristics,
    - port locations,
    - emission factors,
    - engine load override rules,
    - vessel type profiles,
    - other settings files.
- A spreadsheet of model run results [CoelloThesisModelRunResults.xlsx].
- A copy of a paper published during the course of this project (Coello et al., 2015) [Coello_etal_2015_AIS_fishing_industry_emissions_inventory.pdf].

UNIVERSITY OF Southampton

Academic Thesis: Declaration Of Authorship

I, Jonathan Coello declare that this thesis and the work presented in it are my own and has been generated by me as the result of my own original research.

"Using AIS data to calculate emissions inventories for small commercial watercraft"

I confirm that:

1. This work was done wholly or mainly while in candidature for a research degree at this University;
2. Where any part of this thesis has previously been submitted for a degree or any other qualification at this University or any other institution, this has been clearly stated;
3. Where I have consulted the published work of others, this is always clearly attributed;
4. Where I have quoted from the work of others, the source is always given. With the exception of such quotations, this thesis is entirely my own work;
5. I have acknowledged all main sources of help;
6. Where the thesis is based on work done by myself jointly with others, I have made clear exactly what was done by others and what I have contributed myself;
7. parts of this work have been published as:

   Coello, J., Williams I., Hudson, D., Kemp, S. (2015) An AIS-based approach to calculate atmospheric emissions from the UK fishing fleet. *Atmospheric Environment,* 114.

Signed: ………………………………………………………………………

Date: ………………………………………………………………………

Acknowledgements

Before undertaking a PhD I thought that it would be challenging. I didn't know the half of it! It's been a rollercoaster rider during which I discovered new interests and developed many skills but also made choices that resulted in a slow and painful last leg of the journey during which I have juggled professional, personal and academic commitments with varying degrees of success. Without the help and support of others, this thesis most certainly would not have made it to print. For this support, I am eternally grateful.

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1 Introduction

An ever-growing body of scientific knowledge suggests that emissions of greenhouse gases (GHGs) and other climate-altering gases and particles could have catastrophic consequences for humanity and the global environment if they are not reduced dramatically in coming years. The primary cause of GHG emissions from anthropogenic activities is the burning of fossil fuels for energy (IPCC, 2014).

It is thought that the most damaging effects of climate change can likely be avoided if global mean temperatures are prevented from rising by more than between 1.5°C and 2°C above preindustrial levels (IPCC, 2014; United Nations, 2016). The Paris Agreement, which came into force in 2016, is the first legally binding international agreement aimed at keeping the rise in mean global temperatures compared to preindustrial levels well below 2°C (United Nations, 2016). In order to achieve this, global emissions of GHGs must be reduced by at least 40%, and possibly as much as 70%, compared to 2010 rates of emissions, by 2050 (IPCC, 2014). This will require reductions in GHG emissions across all sectors, requiring a widespread reduction in the use of fossil fuels as a source of energy (IPCC, 2014). In order to monitor progress and develop effective mitigation strategies, robust emissions accounting practices are essential (United Nations, 2016).

In addition to the climate altering effects of GHG emissions, burning fossil fuels also releases air pollutants that have been associated with a number of non-communicable diseases such as heart disease, stroke, lung diseases and cancers. The World Health Organisation (WHO) estimates that approximately 13% of cardiovascular disease is caused by ambient air pollution and that as many as 2.8 million premature deaths occur annually due to poor ambient air quality. The WHO also states that reducing transport emissions is one of the best mitigation measures available for improving outdoor air quality (WHO, 2017).

Before the 1990s, shipping's contribution to atmospheric pollution was afforded little attention by researchers or policy makers (Schrooten et al., 2008). However, research conducted over the past two decades has highlighted that shipping is a significant contributor to emissions of GHGs (predominantly CO_2), nitrogen oxides (NO_X), sulphur dioxide (SO_2) and particulate matter (PM), all of which contribute to human perturbations of the Earth's radiation budget, resulting in a complex and uncertain effect upon the climate (Buhaug et al., 2009; Coggon et al., 2012; Eyring et al., 2010; Lawrence & Crutzen, 1999; Jalkanen et al., 2014; Smith et al., 2014). In addition to the climate altering effects of shipping emissions, NO_X, SO_2 and PM have negative effects upon air quality, human health and aquatic and coastal environments (Bartnicki et al., 2011; Deniz & Durmuşoğlu, 2008; Eyring et al., 2010; Schrooten et al., 2008). Since 2005, the IMO MARPOL Annex VI regulations have been in force as the main international instrument for the control of atmospheric pollution emissions from the shipping industry (IMO, 2018).

The most comprehensive inventory of shipping emissions compiled to date was produced by the International Maritime Organisation (IMO). The *Third IMO GHG Study 2014* (Smith et al., 2014) presented estimates that, in 2012, the global international and domestic shipping industry emitted 949 million tonnes of CO_2 and 972 million tonnes of combined CO_2, methane (CH_4) and nitrous oxide (N_2O), expressed as CO_2-equivalent (CO_2e). Combined CO_2e emissions are calculated using 100-year global warming potential conversion factors from the IPCC Fifth Assessment Report (AR5) (IPCC, 2013).

Over the five years from 2007 to 2012 shipping's contribution to total anthropogenic GHG emissions has reduced from 3.2% to 2.5% (Smith et al., 2014). This indicates a small reduction from the figures presented in the *Second IMO GHG Study 2009* of 1046 million tonnes of CO_2 emitted by the global shipping industry in 2007 (Buhaug et al., 2009). However, this reduction is attributed to a global dip in economic activity rather than a meaningful improvement in the environmental performance of the shipping industry (Smith at al., 2014). The observed reduction of shipping emissions throughout this time resulted from a wide-spread adoption of slow steaming, the practice of cruising at slower speeds to improve efficiency and reduce fuel consumption. This happened due to a combination of high fuel prices and overcapacity of the cargo fleet caused by reduced demand for international freight transport (Smith at al., 2014; Halff, 2017).

The widespread practice of slow steaming seems to have survived a reduction in oil price. However, it is likely that the practice will become less popular as demand for international freight transport increases (Halff, 2017). Overall, the downward trend in shipping emissions is expected to reverse in the long-term as global economic activity increases (Smith et al., 2014).

The shipping industry also contributes disproportionately large fractions of global anthropogenic NO_X, SO_2 and PM emissions, with NO_X and SO_2 contributions by the shipping industry making up 15% and 13% of anthropogenic totals, respectively (Smith et al., 2014).

These pollutants have a complex effect upon the climatic system and can lead to both warming and cooling as a result of increased marine aerosol and cloud formation (Coggon et al., 2012). Lauer et al. (2007) postulate that these effects are likely to result in a net short-term cooling effect upon the climate as a result of shipping activities. In the longer-term, however, the global warming caused by GHGs is forecast to become the shipping industry's dominant effect on the climate (Eyring et al., 2010).

International climate agreements such as the Paris Agreement have avoided setting targets for international shipping (United Nations, 2016). This is large due to a lack of consensus on a fair approach for the allocation of emissions to nations (Gilbert & Bows, 2012). Instead, the IMO has been tasked with agreeing and implementing a strategy for reducing GHG emissions from the shipping sector as a whole (United Nations, 2016).

Some progress has been made by the IMO towards this aim through the MARPOL Annex VI regulations on air pollution from shipping (IMO, 2018). Since 2011, the Energy Efficiency Design Index (EEDI) and Ship Energy Efficiency Management Plan (SEEMP) have been in effect. The EEDI requires new vessels in the most energy intensive ship categories, such as tankers, bulk carriers and container ships to meet increasingly strict energy efficiency targets (gCO_2 /cargo tonne-mile). Targets are made more stringent every five years, with plans for new vessels in 2025 to be 30% more efficient than equivalent vessels in 2010 (IMO, 2016a). However, some vessel types, e.g. fishing vessels, are not covered by the EEDI. The EEDI also generally only applies to relatively large vessels, with less strict, if any, requirements on smaller vessels in each regulated category.

The SEEMP targets improving energy efficiency of vessels already in operation, and applies to all IMO regulated vessels of 400 GT and above that operate internationally. Every qualifying vessel was required to have a SEEMP from the beginning of 2013. Guidance is offered on the measurement of vessel energy efficiency with the provision of tools such as the Energy Efficiency Operational Indicator (EEOI). However, there are no mandatory energy efficiency improvements that vessel operators must make under the SEEMP and so it serves only as a mechanism to encourage good practice rather than enforcing it (IMO, 2016a).

In 2016 the IMO also introduced a new requirement under the SEEMP, which came into force from the start of 2018 for all vessels over 5000 GT to report annual fuel use by main and auxiliary engines to their flag state. These reports are anonymised and aggregated and submitted to the IMO Fuel Oil Consumption Database. These data will underpin IMO decision making for more effective regulation of GHG emissions from the shipping sector by 2023 (IMO, 2016b). At present, however, widespread opinion is that too little progress is being made toward reducing the emission of GHGs from the shipping industry, an issue that has been a source of criticism for the IMO (Harvey, 2016).

Research by the International Transport Forum (2018) shows that a reduction of between 82% and 95% of projected fuel consumption and emissions is possible by 2035. This could be achieved through a switch to alternative fuels, including biofuels; use of electric and wind-assisted propulsion; operational measures such as slow steaming and improved port efficiency; and the use of efficient hull designs, air lubrication and bulbous bows. A shift towards larger vessels will also help to reduce the overall environmental impact of the sector.

The slow progress that has been made to date has led to suggestions by the European Union (EU) that shipping emissions should be included in the EU Emissions Trading Scheme. This is a controversial suggestion than some believe may hinder efforts to agree a global strategy for the reduction of emissions from the shipping industry (ECSA, 2018). Underlining the importance of agreeing and implementing an effective global regulatory system is the IMO prediction that the growth in international trade over the coming decades will result in an increase in GHG emissions from shipping activities of between 50% and 250% by 2050 even with an anticipated 40% improvement in energy efficiency (Smith et al., 2014).

By comparison, more progress has been made to regulate other atmospheric pollution emissions from the shipping sector. Under MARPOL Annex VI, emissions of SO_2 and PM have been reduced significantly through the introduction of fuel quality regulations. The current maximum sulphur content of marine bunker fuel oil is 3.5%, which is due to be reduced to 0.5% in 2020. There are also a number of emission control areas (ECAs) where fuel sulphur content is further limited to 0.1%. Technical regulations for marine diesel engines are also in place that control emissions of NO_x, with ECAs where even stricter regulations are enforced (IMO, 2018).

For all pollutants, estimates of the quantity and location of emissions are important for both the evaluation of impacts and when assessing different emission control options, creating policy and monitoring the effect of implemented mitigation measures (Endresen et al., 2008; Gilbert & Bows, 2012; Miola & Ciuffo, 2011; Miola et al., 2010; Tzannatos, 2010).

For emissions inventories to be useful, they must be repeatable and practicable so that they can be systematically applied and trends over time can be detected (Williams et al., 2012). For effective policy measures to be designed and implemented, emission accounting and apportionment to sub-global regions must be done consistently and reliably (Gilbert & Bows, 2012). Disagreement about the methods used to allocate shipping emissions to nations is one of the major factors that has inhibited the development of effective global shipping emissions mitigation policy by the IMO (Gilbert & Bows, 2012).

There are two broad approaches that have been applied to compiling inventories of atmospheric emissions from the shipping industry, which can be described as fuel-based and activity-based. Fuel-based approaches use aggregated fuel use statistics, usually compiled from sales and tax records, to calculate emissions using fuel-based emission factors (Endresen et al., 2005; 2007; Skjølsvik et al., 2000). Activity-based approaches calculate emissions from data on ship design characteristics, activity-profiles and activity- and technology-specific emission factors (Buhaug et al., 2009; Corbett & Köhler, 2003; Endresen et al., 2003; 2007; Eyring et al., 2005; Psaraftis & Kontovas, 2009).

In recent years, activity-based approaches have been favoured as they are considered more accurate due to inconsistent reporting of fuel statistics, creating doubt over the validity of fuel-based methods (Buhaug et al., 2009; Corbett & Köhler, 2003; Psaraftis & Kontovas, 2009). Fuel-based methods are also insufficient for meaningful allocation of emissions to nations (Gilbert & Bows, 2012). Activity-based methods also offer advantages when creating spatially- and temporally-resolved emissions inventories and forecasting future emissions trends (Buhaug et al., 2009; Eyring et al., 2005; Smith et al., 2014; Wang et al., 2008).

Uncertainty associated with the activity data inputs to activity-based methods has been considerable in the past, leading to significant differences in the results modelled (Corbett & Köhler, 2003, 2004; Endresen et al., 2003, 2004). More recently, the availability of high quality activity data that has resulted from technological advancements such as the introduction of the Automatic Identification System (AIS) has allowed for the development of new activity-based emissions modelling approaches with significantly reduced uncertainty and greater spatial and temporal precision (Jalkanen et al., 2009; 2012; 2014; MARIN, 2012; Olesen et al., 2009; Smith et al., 2014).

Activity-based approaches are, however, limited by the availability of vessel technical data as only reasonably well inventoried vessel populations can be modelled. The majority of activity-based emissions inventories have used the IHS-Fairplay (formerly Lloyds Register Fairplay) database of IMO-registered commercial vessels (Buhaug et al., 2009; Corbett & Kohler, 2003; Endresen et al., 2003, 2007; Eyring et al., 2005; Paxian et al., 2010; Psaraftis & Kontovas, 2009; Smith et al., 2014). This database contains vessels registered with the IMO. Significantly, IMO registered vessels are generally ocean-going commercial vessels with a gross tonnage (GT) of at least 100 GT (Endresen et al., 2007, 2008; Eyring et al., 2010; Schrooten et al., 2008).

A thorough review of the literature has identified that very little research has been undertaken that satisfactorily quantifies the emissions of GHGs and other atmospheric pollutants caused by small commercial watercraft under 100 GT. Activity-based emissions inventories tend to omit emissions from recreational, small commercial (<100 GT) and military vessels entirely (Endresen et al., 2007). Rough estimates put the extent of this omission at around 5-10% of global shipping emissions (Endresen et al., 2007; Whall et al., 2010). The fact that the EEDI and SEEMP target larger vessels (IMO, 2016a) also implies that, while energy efficiency of large vessels will improve, small commercial watercraft are unlikely to see significant energy efficiency improvements; this is likely to mean that their relatively contribution to the environmental impact of shipping activities will increase in the future.

One reason for this is that AIS transponders are only mandatory for vessels of at least 300 GT engaged in international voyages, cargo ships of at least 500 GT engaged in domestic voyages and all passenger ships under the Safety of Life At Sea (SOLAS) convention (IMO, 2002). However, affordable AIS transponders are available for non-SOLAS vessel such as recreational and small commercial watercraft (e.g. ICOM, 2013), and the safety benefits offered are likely to result increasing voluntary uptake (Jalkanen et al., 2014). This is a valuable source of data for quantifying the atmospheric pollution caused by small commercial watercraft.

Although AIS transponders are installed on recreational and small commercial vessels, only one attempt (Jalkanen at al., 2014) has so far been made to use this data for modelling emissions from these vessels, which had clear limitations. The inventory includes small vessels that have AIS transponders but does nothing to address the omissions of small vessels without AIS transponders. Very broad-brush assumptions about vessel technical specifications are also made, with all vessels being assigned the engine characteristics of tugboats. Given that tugboats only make up a proportion of small vessels, and given that they also tend to have high-powered engines for their size, this assumption is likely to lead to an overestimate of emissions.

This thesis presents the development of a new activity-based methodology for the calculation of atmospheric pollution emissions from small commercial vessels. The method uses AIS data, a high-quality source of activity data for the estimate of fuel use and emissions from shipping activities. It is not mandatory for all small commercial vessels to use AIS technology, so AIS data is only available for a subset of small commercial vessels. Therefore, this thesis also tackles methods for using the available AIS data as a representative sample of vessel activity. An inventory of emissions caused by the UK fishing fleet over a year is calculated as a case study of the method's use. The sensitivity of emissions calculated using the methods developed in this thesis to various input data are quantified and the uncertainty in the final estimate is calculated.

This thesis does not cover emissions allocation in depth. Given that the case study fleet is made up of UK fishing vessels, it is assumed that all emissions from the fleet can be attributed to the UK. Due to limited availability of AIS data free of charge, and the cost of obtaining more AIS data, emissions were only calculated for the case study fleet of UK fishing vessels for one year to showcase the methodology. This research is also limited to the direct emission of GHGs and atmospheric pollutants as a results of fuel combusted in the engines of vessels. All indirect emissions associated with the sector are outside of the scope of this project.

1.1 Aims and objectives

The aim of this thesis is to develop a methodology that can be used to address the omission of small commercial watercraft from shipping emissions inventories.

Objectives:

1. To review previously used methodologies for the production of atmospheric emissions inventories for shipping activities and assess their applicability to small commercial watercraft.

2. To create a robust, repeatable and practical methodology for the calculation of atmospheric pollution caused by small commercial watercraft.
3. To identify sources of uncertainty that affect the emissions calculation methodology developed and undertake a rigorous sensitivity and uncertainty analysis.
4. To calculate an emissions inventory for a case study fleet of small commercial vessels and assess the validity of results.

1.2 Overview of content

This thesis is laid out over five main chapters, excluding this introductory chapter and the final conclusions. Chapter 2 contains a comprehensive review of the methods published in the body of academic literature that have been used to quantify atmospheric pollution emissions from the shipping industry. The methodologies are summarised, compared and categorised and their relative merits and drawbacks are identified and highlighted. Their applicability to the production of emissions inventories for small commercial watercraft is also assessed.

In Chapter 3, the methodology and software tool developed throughout this research are described in detail. This is a new activity-based emissions calculation methodology for the production of emissions inventories for small commercial watercraft from incomplete AIS data records. The methodology builds upon previous AIS-based emissions inventory methods but breaks new ground in the use of activity sampling rather than direct one-to-one matching of AIS tracks. A novel methodology is introduced for detecting and modelling operating conditions such as trawling and dredging by fishing vessels. A new combined speed calculation methodology is also introduced and trialled for estimating vessel speed from both the distance travelled between consecutive AIS data points and the speed values recorded directly in the AIS data.

Chapter 4 covers the refinement of the activity sampling method used to associate the AIS data that describe vessel activity with the modelled fleet of vessels when insufficient data are available to match vessels to AIS data records on a direct one-to-one basis. Fleet representativeness, filtering of unsuitable AIS tracks, geographic relevance and the introduction of undesired bias are considered in detail and sampling criteria are suggested for the case study fleet of UK fishing vessels.

In Chapter 5, sensitivity analysis is used to understand the effect that uncertainty in model inputs have upon the results calculated. The most significant sources of uncertainty are identified and potential bias in results is discussed. A Monte Carlo uncertainty analysis is also undertaken and the overall uncertainty in the emissions inventory is quantified. The results of this chapter are also used to calibrate input parameters for modelling of emissions for the case study fleet.

Chapter 6 contains the results of two methods used to calculate an annual emissions inventory for the UK fishing fleet. The AIS-based methodology and software tool developed during this project are used to calculate disaggregated emissions for the different vessel classes that make up the UK fishing fleet and to produce geographic mappings of emissions. To corroborate these results, a fuel-based methodology using published fuel use rates per unit catch and total catch landed by the UK fishing fleet is used to produce aggregate emissions for comparison with the new emissions calculation methodology developed.

2 Methodological review

The purpose of this chapter is to review the academic and industry literature on methodologies used to calculate atmospheric emissions generated by ships for the production of emissions inventories. The methods are categorised and assessed to determine their applicability to the calculation of emissions from small commercial watercraft. This chapter satisfies objective 1 of this project:

> *"To review previously used methodologies for the production of atmospheric emissions inventories for shipping activities and assess their applicability to small commercial watercraft."*

2.1 Introduction

A range of methodologies have been used to calculate emissions of atmospheric pollutants and GHGs over the past two decades. These can be broadly separated into two categories:

- Fuel-based emissions inventories, which take fuel sales statistics or surveyed fuel usage data as their main data input (Benkovitz et al., 1996; Corbett et al., 1999; Olivier et al., 1996; Skjølsvik et al., 2000), and
- Activity-based emissions inventories, which use information about shipping activities and vessel characteristics to compute an estimate of fuel consumption and associated emissions (Buhaug et al., 2009; Fitzgerald et al., 2011; Smith et al., 2014; Trozzi et al., 2016).

Emissions inventories for shipping are calculated for a variety of reasons. These can be categorised into four main groups: 1) as inputs to radiative forcing models for determining climate impacts (Capaldo et al., 1999; Eyring et al., 2010; Lauer et al., 2007; Lee et al, 2006), 2) to model impacts upon human health (Corbett et al., 2007; Dalsøren et al., 2007; Winebrake et al., 2009), 3) for national or regional emissions accounting (Entec, 2005; Wang et al., 2007; Whall et al., 2002; 2007; 2010) and 4) for the evaluation and tracking the progress of technological, operational and policy measures for mitigating the environmental impacts of shipping (Buhaug et al., 2009; Farrell et al., 2003; Jalkanen at al., 2014; Lindstad et al., 2011, 2012; Ma et al., 2012; Smith, 2012; Smith et al., 2014; van Vuuren et al., 2009; Vergara et al., 2012; Wang & Corbett, 2007; Wright et al., 2011). Groups 1 and 2 are predominantly the concern of academic researchers, while groups 3 and

4 are of greater concern to national and international governing bodies due to their importance for emissions accounting and mitigation strategy evaluation.

In order to be useful, emissions inventories should be as accurate as practicably possible given time and resource constraints, geographically and temporally resolved, and capable of facilitating the assessment of mitigation options by reflecting changes in vessel technology, fuel types and operating practices (Williams et al., 2012). A reasonable level of accuracy is necessary for all emissions inventory uses outlined above. Geographical and temporal resolution of emissions is necessary for modelling air quality, human health and pollution deposition impacts of shipping emissions (Bartnicki et al., 2011; Corbett et al., 2007; Dalsøren et al., 2007; Winebrake et al., 2009), and the cloud forming climatic effects of shipping emissions (Coggon et al., 2012; Lawrence & Crutzen, 1999; Song et al., 2003).

For policy and emissions accounting purposes, emissions can also be allocated to nations and regions in a variety of ways ranging from the flag of vessels, the location of fuel sales or the origin/destination of voyages or cargo. The quantity of emissions allocated to different nations or regions differs substantially between the different emissions allocation strategies, as shown by Gilbert & Bows (2012).

Each methodological approach will be evaluated in terms of the type of emission factors that can be applied, the ability to create geospatially and temporally resolved emissions inventories, the flexibility of the approach for emissions allocation, and the usefulness in terms of modelling the effects of technological and operational changes. The approaches will also be assessed for their applicability to the calculation of emissions from small commercial vessels.

2.2 Emission factors

A common element of all methodologies is the need for emission factors, which are used to calculate a mass of emissions of a pollutant from a given mass of fuel combusted, or power produced by an engine (Trozzi et al, 2016). Pollutants and GHGs in ship exhaust plumes can be categorised into two main groups based on the type of emissions factors used to model them.

All pollutants and GHG emissions rates are influenced by the chemical composition of the fuel being combusted. Some emissions are solely determined by fuel chemical composition, such as carbon dioxide (CO_2) and sulphur dioxide (SO_2). These can be accurately quantified with no more information than the mass of fuel combusted and appropriate emission factors. Other pollutants, however, are emitted at rates that also depend on the conditions of combustion, which vary between types of engines, engine age and condition, and as the loading on the engine varies during use. These pollutants include oxides of nitrogen (NO_X), carbon monoxide (CO), volatile organic compounds (VOCs) and particulate matter (PM) (MARIN, 2012; Trozzi et al., 2016). In addition to the mass of fuel consumed and appropriate emission factors, modelling these emissions accurately requires information on the vessel's engine loading while the fuel was combusted.

Emission factors that only vary depending on fuel chemistry and combustion rate will be referred to as *fuel-specific* emission factors. Those that vary also with the conditions of combustion will be referred to as *technology-specific* emission factors.

Fuel-specific emission factors are calculated based on chemical analysis of fuels and fundamental chemical principles (Buhaug et al., 2009; Endresen et al., 2005; Trozzi et al., 2016). Technology-specific emission factors are usually calculated from testing of engines in a manufacturer's test-bed environments (e.g. Köhler, 2003) or by monitoring engines installed aboard vessels during operation (Agrawal et al., 2008a, 2008b, 2010; Cooper, 2003a, 2003b, 2005; Jüttner et al., 1995; Kasper et al., 2007; Smith et al., 2014; Winnes & Fridell, 2010).

Fuel-specific emission factors are simply multiplied by the quantity of fuel that is consumed by a given vessel population over a defined period of time to yield a mass of emissions. The way in which technology-specific emission factors are applied is more varied depending on the emission calculation methodology used. Three tiers of technology-specific emission factors can be identified (Table 2.1) (Trozzi et al., 2016). Tier 3 emission factors are true technology-specific emission factors. Lower tier emission factors are derived from technology-specific emission factors using assumptions about technologies installed within a vessel population and vessels' engine load profiles. Given that lower tier emission factors are derived from the state of vessel engine technology at a specific time, their applicability will decline as they age and the vessel population is replaced.

Table 2.1. Types of technology-specific emission factor (after Trozzi et al., 2016; Whall et al., 2007).

Tier	**Description**
Tier 1	Assumed or calculated percentage of different engine-types installed within a population of vessels and an assumed typical engine loading profile are used to determine a general emission factor for each pollutant that can be multiplied by the mass of fuel burnt to calculate emissions.
Tier 2	A vessel population is divided into groups with similar engine characteristics. An assumed load profile is used to generate engine-type-specific emission factors that are derived from assumed engine loading profiles for these vessel groups.
Tier 3	Vessel activity and engine loading are modelled explicitly, which means an emission factor that is specific to the engine type and load can be used to calculate emissions.

Effort, Cost, Certainty

There are differences in the way Tier 3 emission factors are applied. Some guidance documents, such as the *EMEP/EEA air pollutant emission inventory guidebook 2016* (Trozzi et al., 2016), provide emission factors for different journey-phases, such as at-berth, manoeuvring and cruising, with assumed engine loads for each of these trip phases (Trozzi et al., 2016). Another approach is to provide a table of correction factors for a broad spectrum of engine loads to be applied to a single emission factor for each pollutant (De Meyer et al., 2008; Gommers et al., 2007; MARIN, 2012; Smith et al., 2014).

Methods used for compiling emissions inventories can be broadly categories based on the approach used to quantify fuel consumption, whether the approach uses aggregated (top-down) or vessel-level (bottom-up) data, and the tier of emission factors that can be applied. The tier of emission factors that can be applied depends largely upon the method used for modelling fuel consumption. The emissions inventory calculation techniques reviewed in this chapter are categorised on this basis.

Due to the increasing uncertainty associated with lower tier emission factors, emissions inventory calculation methods that use higher tier emission factors are likely to be more accurate. However, the accuracy improvements will only apply to pollutants that use technology-specific emission factors and higher tier methods may require data that are more difficult and costly to obtain. It is also likely to be more time-consuming to develop the methodologies required to apply higher tier emissions factors. Therefore, the selection of method should be determined based on an evaluation of the intended uses of the emissions inventory, the pollutants to be included, and the availability of data and resources for the delivery of the project.

2.3 Emissions Inventory Methods

A review of the current body of literature regarding shipping emissions inventory calculation has identified six distinct groups of methodologies, and a classification terminology has been developed to describe these. The terminology used will be explained here to avoid confusion given that there is some inconsistency in the use of terminology within the literature on the subject. For the purposes of this review, the terminology will be used as outlined in Table 2.2.

Table 2.2. Terminology used to define emissions inventories.

Term	**Meaning**
Top-down	Based on aggregate fuel-use or activity data pertaining to an entire vessel population or large subgroups of a vessel population.
Bottom-up	Based on fuel-use or activity data modelled or sampled for individual vessels.
Fuel-based	An emissions inventory that uses either data on fuel sales or direct data on fuel consumption as the main input to emissions calculation.
Activity-based	An emissions inventory that uses direct activity-data such as the number of hours vessels operate and the speed of vessels during operation as the major input to fuel use and emissions calculation.
Proxy-activity-based	An emissions inventory based on indirect activity data such as cargo tonne-kilometres rather than direct vessel activity data.
Measurement-based	An emissions inventory estimated from atmospheric sampling.

2.3.1 Top-down fuel-based methods

The earliest studies into the emissions of atmospheric pollutants from shipping activities used international statistics on the quantities of fuels sold to determine the total amount of fuel consumed by the shipping industry (Benkovitz et al., 1996; Corbett et al., 1999; Olivier et al., 1996; Skjølsvik et al., 2000). In more recent studies this method has been used alongside activity-based methods as a means of comparison and validation (Buhaug et al., 2009; Committee on Climate Change, 2011; Smith et al., 2014).

Theoretically, shipping emissions are calculable from maritime bunker fuel sales statistics, which are compiled by organisations such as the International Energy Agency (IEA), Energy Information Administration (EIA) and the UNFCCC (Olivier et al., 1996; Skjølsvik et al., 2000; Smith et al., 2014). If these figures were reliable, they would be one of the better sources of data available for quantifying aggregated emissions of pollutants from international and domestic shipping activities (Psaraftis & Kontovas, 2009).

Unfortunately, these data are suspected to be relatively inaccurate as a result of under-reporting and misallocation of fuel sales (Corbett & Köhler, 2003; Gilbert & Bows, 2012; Schrooten et al., 2008), and inconsistencies in the definition of reporting categories (Psaraftis & Kontovas, 2009). For example, the IEA changed their definition of international bunkers from including military ships and aeroplanes to excluding them in 2006 (IEA, 2011). Fuel consumption by fishing vessels also tends to be reported in an aggregated form with other agricultural activities (Endresen et al., 2007), reducing the usefulness of these information sources.

Comparison of international shipping emissions inventories based on fuel-sales statistics with activity-based emissions inventories has led researchers to the conclusion that using international bunker fuel sales as a primary model input leads to significant underestimation of emissions (Buhaug et al., 2009). This is thought to be a result of failure to report all sales, misallocation of fuel sales to other sectors, and wrongly allocating marine fuel sales for international navigation purposes to domestic navigation (Buhaug et al., 2009; Corbett & Köhler, 2003, 2004). This is despite an apparent economic driver for companies involved in the sale of both international and domestic bunker fuels to over-report sales of international fuels, as these sales are not subject to fuel duties (Schrooten et al., 2008).

Even if fuel sales statistics were reliable, their use as the basis for emissions inventories presents other challenges. For pollutants for which emissions must be calculated using technology-specific emission factors, only Tier 1 generalised emission factors can be applied without the use of additional datasets (Trozzi et al., 2016). Additional information regarding the engines installed across the vessel population in question could be used to estimate the quantity of fuels used in each type of engine in order that Tier 2 emission factors can be used (Corbett et al., 1999; Skjølsvik et al., 2000). Nevertheless, a degree of uncertainty in the emissions inventory will arise from the use of lower tier technology-specific emissions factors.

Another difficulty encountered when using a fuel-based methodology is the geographical allocation of emissions. There is good evidence to suggest that the location where fuel is purchased does not reliably represent where the fuel is used. For example, allocation to nations based on fuel sales results in considerable discrepancies with other emissions allocation methodologies (Entec, 2005; Gilbert & Bows, 2012; Heitman & Khalilian, 2011). For this reason, top-down fuel-based emissions inventories either have to be presented in aggregated form (e.g. Endresen et al., 2007), or must use a proxy of vessel activity to estimate the geographical distribution of emissions (Corbett et al., 1999; Olivier et al., 1996; Skjølsvik et al., 2000).

Two vessel activity proxies that have been used in various studies are the Automated Mutual-Assistance Vessel Rescue System (AMVER) dataset and the Comprehensive Ocean-Atmosphere Data Set (COADS). The AMVER exists as a safety system to track merchant vessels at sea and to automatically notify nearby vessels and emergency services in case of disaster. Participation in the system is voluntary. The database includes daily submissions, including geographical location and intended course, from merchant vessels at sea. Use of the system is generally restricted to merchant vessels of 1000 GT or greater engaged in voyages of 24 hours or more (Buhaug et al., 2009; Endresen et al., 2003). The COADS is a scientific dataset of meteorological observations maintained by the National Centre for Atmospheric Research (NCAR) and National Oceanic and Atmosphere Administration (NOAA). The main source of data is the Voluntary Observing Ships (VOS) fleet, which are predominantly research vessels (Buhaug et al., 2009; Endresen et al., 2003).

Relative reporting frequency within pre-defined grid squares is used as a basis to determine vessel traffic densities from these datasets (Wang et al., 2008). It has been observed that neither dataset gives a particularly accurate representation of world shipping activities. This is partially because of the bias towards certain types of vessel in each dataset. There also appears to be under-reporting in the AMVER system by vessels engaged in coastal shipping, which is probably as a result of voyages often being under 24 hours in duration and lower perceived risk of incidents that would require assistance from vessels other than coastguards (Wang et al., 2008). Some studies have favoured the use of one of these datasets for various reasons (Buhaug et al., 2009; Endresen et al., 2003, Skjølsvik et al., 2000) whereas others have concluded that using combination of both datasets yields the most reliable results (Dalsøren et al., 2009; Wang et al, 2008).

2.3.2 Bottom-up fuel-based methods

Another fuel-based method that has been used for producing emissions inventories is to sample fuel use within a population of vessels using surveys, and to scale the fuel use determined from the sample to represent the wider vessel population. It is debatable as to whether this is a fuel-based or activity-based methodology given that activity data are often used to scale the emissions to the entire population level. For example, Psaraftis & Kontovas (2009) use this approach and refer to it as activity-based. However, for the purposes of this review it has been categorised as a bottom-up fuel-based method given that the key data input is fuel consumption data, rather than fuel consumption being derived from activity data.

Studies employing this method category usually focus on smaller and more specific vessel populations such as fishing vessels (Iribarren et al., 2010; Tyedmers, 2001) and tour boats (Byrnes & Warnken, 2009). A notable exception is work by Psaraftis & Kontovas (2009), who applied this methodology to calculating emissions from the entire commercial fleet of vessels of 100 GT and larger, using Lloyd’s Register data to scale 375 survey responses across various vessel type and size categories to produce an estimate of global atmospheric pollution emissions.

Bottom-up fuel-based methods have been the primary approach used for the quantification of fuel consumption and atmospheric emissions from fisheries. Various studies have used surveys of vessel operators to determine fuel use and catch for various vessels. These results are then scaled up using data on total landings to determine total emissions (Curtis et al., 2006; Iribarren et al., 2010; Tyedmers, 2001). A similar approach used surveys of fuel use and activity time to estimate emissions from Australian tour boats (Byrnes & Warnken, 2009) and tugs and dredgers (De Meyer et al., 2008). Fuel use surveying has also provided useful data for the estimation of emissions from ships at berth, an area of significant uncertainty (Hulskotte & van der Gon, 2010).

This type of approach has some advantages compared to top-down fuel-based methods. Notably, there are no economic drivers for under-reporting or misallocation of fuel use by survey participants, meaning that the results are less likely to be biased. These types of study also generate useful secondary data for use in future emissions inventory initiatives. These approaches do, however, have limitations in terms of applying Tier 3 emission factors as data on engine load profiles are not collected.

Spatial allocation of emissions inventories generated using this type of method requires use of proxy data given that specific vessel routes are unlikely to be captured in surveys. Exploration of the effects of technological and operational changes will also be limited to technologies that are already installed and available for sampling. Operational changes will be difficult to model using survey data alone.

2.3.3 Top-down activity-based methods

Upon the realisation that fuel sales statistics are not necessarily a reliable source of data due to errors of reporting and misallocation, a new type of methodology evolved. This used data on vessel design characteristics, operating times and engines loads to calculate fuel consumption and emissions of atmospheric pollution. General formulae for calculating emission of a given pollutant from an engine are given in Equations 2.1 and 2.2 (Trozzi et al., 2016).

$$E = FC * EF = T * P * LF * SFOC * EF \quad \text{Eq. 2.1}$$

$$E = FC * EF = T * P * LF * EF \quad \text{Eq. 2.2}$$

where:

E = emissions (kg),

FC = fuel consumption (kg),

EF = emission factor (g/kg fuel or g/kWh energy produced),

T = time engine is in operation (hr),

P = nominal power of engine at 100 % of Maximum Continuous Rating (MCR) (W),

LF = load factors, i.e. the percentage of an engine’s nominal power being utilised (% MCR),

$SFOC$ = specific fuel oil consumption, i.e. the rate at which fuel is consumed by an engine (g/kWh).

When using emission factors expressed as emissions per unit of fuel consumed, Equation 2.1 is used. For emission factors expressed per unit of power produced by the engine, Equation 2.2 is used. Formulae similar to these have been used in the vast majority of activity-based shipping emissions inventories to compute emissions for both main and auxiliary engines for cruising, manoeuvring, loading and unloading, and hotelling activities (Buhaug et al., 2009; Corbett & Köhler, 2003; Endresen et al., 2003, 2007; Eyring et al., 2005; Whall et al., 2002, 2007, 2010). Hotelling is the term used for the running of systems and equipment on-board for crew and passenger living while a vessel is docked or at anchor.

Top-down activity-based inventories work at an aggregated fleet level, applying common values for T, P, LF and SFOC to groups of vessels of similar type and size (Buhaug et al., 2009; Corbett & Köhler, 2003; Dalsøren et al., 2009; Endresen et al., 2003). The IHS-Fairplay or Lloyd's Marine Intelligence Unit (LMIU) vessel characteristics databases (previously the Lloyd's Register and Lloyd's Register-Fairplay database) are used to categorise vessels by type, size, age, and engine characteristics. For each category of vessels, average or total engine power (P) is calculated, average or total time at sea (T) is estimated, and average engine load factors (LF) are estimated. Standard SFOC and EF values are chosen from the various sources available (e.g. Trozzi et al., 2016; Whall et al., 2002) and applied to calculate emissions for each category of vessels.

The differences between the methods are in the way that figures for T and LF are determined. Earlier studies determined these data using the expert judgement of people such as vessel operators, marine engineers and engine manufacturers to produce assumptions (Corbett & Köhler, 2003; Endresen et al., 2003). As might be expected, this led to quite varied estimates of fuel consumption and emissions from shipping, resulting in debate as to which assumptions were most realistic (Corbett & Köhler, 2004; Endresen et al., 2004, 2007). Endresen et al. (2007) attempted to improve on this method by estimating the number of days at sea that would be required for 'average' cargo vessels of various types to meet demand for global cargo transport based on cargo movement data.

The LMIU provides data on port arrivals of commercial vessels ≥100 GT, which have been used by Dalsøren et al. (2009) to estimate the number of days at sea. There is still relatively high uncertainty in this estimate as port visits in the LMIU are recorded by date rather than time, meaning that estimating the duration of each trip is subject to significant uncertainty. This is especially significant in the case of passenger ferries operating on short crossings, as only the first call at a port on any given date will be recorded (Whall et al., 2002). These data sources also have the disadvantage of being commercially available products and, therefore, have relatively high associated cost to access.

Ferry timetables have been used by some researchers to more accurately calculated emissions from short-crossing ferry services (Baird, 2012; Baird & Pedersen, 203). Whilst representing a higher quality source of data for T than pure expert judgement, these methods still apply assumptions about LF for vessels during different journey phases. This is because arrival and departure data are generally not recorded with high enough temporal resolution to reliably calculate vessel speed, from which engine load during journeys can be estimated (e.g. using Equation 2.3).

Other databases on vessel movements are used to determine T in the compilation of emissions inventories. Examples of this are information from national customs organisations on port callings, which can also include information on international vessels' last and next ports of call (Howitt et al., 2010), and information on port callings held by port authorities, which have been used in the calculation of emissions within and around ports (Dong et al., 2002; Chang et al., 2013; Song, 2013; Trozzi et al., 1995; Tzannatos, 2010; Villalba & Gemechu, 2011). These data sources have the advantage of usually being available at no or low cost, but their availability is subject to the willingness of the organisation that owns the data to make them available.

Some top-down activity-based inventories have included emissions from military watercraft using various sources of documented fleet statistics and assumptions about vessel activity (Corbett & Köhler, 2003; Endresen et al., 2003; Eyring et al., 2005). However, due to the absence of reliable vessel activity data sources, military vessels have been excluded from the majority of inventories compiled using activity-based methods (Buhaug et al., 2009; Paxian et al., 2010; Wang et al., 2007; Whall et al., 2002, 2007, 2010).

A significant advance in being able to determine more realistic values for T and LF was the introduction of the Automatic Identification System (AIS), a safety and anti-collision system for ships. The AIS devices that are installed aboard ships automatically broadcast information including the ship's identity, location and speed every few seconds. These broadcasts are received by networks of receiver stations and other vessels (Buhaug et al., 2009). These data were used in the *Second IMO GHG Study 2009* (Buhaug et al., 2009) to determine the average annual days at sea and the average speed of journeys between ports.

In the *Second IMO GHG Study 2009* (Buhaug et al., 2009), journeys were analysed and categorised as either ‘normal’, for journeys with an average speed of over 80% of design speed, or ‘slow’, for journeys with an average speed of less than 80% of design speed. Design speed data contained in the IHS-Fairplay database were used as the basis for comparison. Slow journeys were assumed to be caused by undetected stops into ports while the ship is outside of the AIS receiver network range. Therefore, days at sea were calculated to be the time a vessel would need to travel the distances travelled at ‘normal’ speed.

The average speed of ‘normal’ journeys in relation to the vessel’s design speed was then used to determine the average ‘at sea’ engine load based on the cubic power law. The cubic power law approximately relates relative speed to engine load. A sea margin of 10% was assumed, meaning that design speed was assumed to be reached at 90% of a vessel main engine’s maximum continuous rating (MCR) (Eq. 2.3). The average days at sea and engine load for each vessel type and size category were used to calculate emissions (Buhaug et al., 2009). Note that alternative figures for % MCR at design speed exist in the literature, which are generally 80% or lower (Smith et al., 2013; Traut et al., 2013) to 95% (Lindstad et al., 2011).

$$LF = 0.9 * \left(\frac{V_i}{V_d}\right)^3 \qquad \text{Eq. 2.3}$$

where:

LF = load factor,

V_i = instanteneous speed,

V_d = design speed.

It is worth noting that the cubic relationship between vessel relative speed and engine load is a relatively crude method and more accurate estimates of engine load can be made if the necessary information on ship characteristics are available. Molland et al. (2011) provide a more detailed methodology for the calculation of engine load using more detailed vessel characteristics data.

In terms of producing geographically resolved emissions inventories, because emissions are calculated at an aggregated fleet level, data either need to be presented as an aggregate (Corbett & Köhler, 2003; Endresen et al., 2007), or spatially allocated using proxy data such as AMVER and COADS (Buhaug et al., 2009; Dalsøren et al., 2009; Endresen et al., 2003; Eyring et al., 2005). The use of AIS data enables the calculation of estimates of the time vessels spend engaged in various operations such as cruising, manoeuvring, loading and unloading and hotelling. This means that Tier 3 emissions factors can be used. It is also possible to assess the effect of technological and operational emissions reduction approaches using altered values for T, SFOC, LF and EF for various vessel categories.

2.3.4 Bottom-up activity-based methods

The current state-of-the-art emissions inventory calculation methods are those that use activity and vessel characteristics data for individual vessels to calculate emissions. These fall into two main groups. Those that use known port arrival and departure times and locations to model shipping activities along hypothetical vessel routes (Corbett et al., 2010; De Meyer et al., 2008; Howitt et al., 2010; Paxian et al., 2010; Wang et al., 2007; Whall et al., 2002, 2007, 2010); and those that use actual vessel movements data provided by AIS (Coello et al., 2015; Jalkanen et al., 2009, 2012, 2014; MARIN, 2012; Olesen et al., 2009; Smith et al., 2013, 2014).

Of the group of methods that use hypothetical routes, a Geographical Information System (GIS) model is normally used to process route distances and, based on normal ship service speeds, the time spent in transit. The majority of these models identify the viable sea route with the shortest distance between two ports, avoiding land masses (Corbett et al., 2010; De Meyer et al., 2008; Howitt et al., 2010; Whall et al., 2002, 2007, 2010); one example takes the quickest (shortest time) route between two ports avoiding land masses, taking into account local speed restrictions, such as when passing through canals, and areas of rough sea, which also slow progress (Paxian et al., 2010); another method that has been used is to create a network of shipping lanes using AMVER and COADS data as indicators of where ships tend to operate, and model emissions based on the shortest routes between ports travelling along this pre-constructed network of shipping lanes (Wang et al., 2007).

This is advantageous because empirical data are used to define ship routes and avoids the issues mentioned in Section 2.3.1 of relying on reporting frequency as a proxy for vessel traffic density.

A common source of data for this type of methodology is LMIU data on port arrivals and departures, which is used to determine origin and destination ports, from which days at sea per journey (T) are derived. Other databases can be used for this where available, such as the Arctic Maritime Shipping Assessment (AMSA) database, which contains detailed data on all Arctic shipping activities (Corbett et al., 2010) and information from national customs organisations (Fitzgerald et al., 2011). These sources of data have the advantage over the LMIU of being free to use if agreements can be reached with the administrating organisations for the provision of the data. Ports also commonly gather information about visiting vessels, which can also be used to produce bottom-up emissions inventories of port shipping activity (Berechman & Tseng, 2012).

Vessel characteristics from IHS-Fairplay, or its predecessors are used to determine vessel design speeds, and assumed engine loads (LF) are applied to calculate emissions (Corbett et al., 2010; De Meyer et al., 2008; Paxian et al., 2010; Wang et al., 2007; Whall et al., 2002, 2005, 2010). Emissions are calculated within a geographical modelling environment, meaning that the production of geographically resolved emissions inventories is possible without the use of any additional data. As individual journeys undertaken by individual ships are the basis of the model, it is possible to apply Tier 3 emission factors, albeit with some level of assumption about the time spent engaged in various port activities such as manoeuvring, loading and unloading and hotelling.

Since the availability of high quality AIS datasets, the use of activity data sources LMIU port arrivals and departures has largely ceased for the calculation of shipping emissions inventories. This is because AIS datasets give far more information about vessel location and speed between port visits, thus yielding higher quality results. However, alternative sources of vessel activity data are useful for validation of results. For example, noon reports containing fuel consumption data were used to validate the AIS-based fuel use and emissions calculation methodology used for the *Third IMO GHG Study 2014* (Smith et al., 2014).

The most advanced emissions calculation methods (Jalkanen et al., 2009, 2012, 2014; Smith et al., 2014) make full use of AIS data in the quantification of emissions inventories.

Automatic Identification Systems (AIS) messages containing information about vessels' location, speed, identity and activities are broadcast by transponders installed aboard all oceangoing vessels over 300 GT and a significant number of small commercial and recreational craft that use AIS technology voluntarily. There are two classes of AIS device. Class-A devices are more powerful and are reserved for use by vessels for which the use of AIS technology is mandatory. For voluntary AIS users there are less expensive but also less powerful Class-B devices available (Vesseltracker, 2014), which are aimed at smaller vessels such as private recreational and fishing vessels (MMO, 2013).

The advantages of using AIS data are related to the fact that AIS transponders fitted aboard ships transmit a signal once every few seconds and should be in operation 24 hours a day, 365 days a year. For this reason, times spent in operation and changes in speed can be detected at a high temporal resolution, meaning that engine load estimated from dynamic vessel speed can be used in calculations rather than applying a journey average cruising speed and corresponding engine load. The location of vessels is also recorded with high spatial resolution, meaning that empirical data can be used when producing geospatially resolved emissions inventories (Coello et al., 2015; Jalkanen et al., 2009, 2012, 2014; MARIN, 2012; Olesen et al., 2009; Smith et al, 2014). This means that there is no longer a need of auxiliary datasets such as LMIU, AMVER and COADS for the creation of geospatially resolved emissions inventories. Tier 3 emission factors can also be applied given that actual speed can be used in dynamic load calculation using formulae similar to Equation 2.3. Assumptions are still required to determine specific port activities when stationary, such as loading and unloading and hotelling. Whilst still subject to some assumptions, the level of uncertainty considerably reduced by using AIS data.

There are, however, some challenges in using this kind of data. One of the key issues is that AIS transponders transmit data very frequently, which results in such large quantities of data that processing emissions in such a way as not to involve excessive computation time becomes challenging (MARIN, 2012; Olesen et al., 2009; Smith et al., 2014).

The study conducted by Olesen et al. (2009) to quantify emissions in Danish marine waters reduced processing time by sampling just 24 days throughout the year, comprising a week day and weekend day of every month, and scaling the results up to a full year. This was based on the assumption that the days sampled were representative of normal shipping activity. The method used by MARIN (2012) to calculate shipping emissions from the sea area around the Netherlands reduced processing time by sampling activity once every two minutes, rather than using the entire data set.

Jalkanen et al. (2009) developed a methodology and the Ship Traffic Emission Assessment Model (STEAM) modelling tool that used the entire AIS dataset with a sophisticated engine load calculation approach, incorporating both calm-water and wave resistance for Danish shipping activities in 2007. This highlights that the use of powerful computers and efficient algorithms can reduce processing times to acceptable levels.

The STEAM modelling tool was subsequently extended to create STEAM2, which uses a more accurate resistance calculation methodology, resulting in more accurate PM and CO emissions estimates, and the functionality necessary to model abatement technologies (Jalkanen et al., 2012). The STEAM2 modelling tool was used to compute an emissions inventory for the period from 2006 to 2009 in the Baltic Sea area (Jalkanen et al., 2014).

In the *Third IMO GHG Study 2014* (Smith et al., 2014), raw AIS data were pre-processed to produce hourly average activity data for each vessel involved in the study, thus reducing the computational overhead such that the full global emissions inventory can be calculated using non-super-computer hardware. The time involved in produced emissions inventories even with this rationalisation of input data is reported as considerable (Smith et al., 2014). The *Third IMO GHG Study 2014*, nevertheless, represents the most advanced methodology for emissions inventory calculation for waterborne vessels thus far.

One significant issue associated with the use of AIS data collected by coastal receiver stations is that ships must be within range of AIS receiver stations in order for the data they transmit to be logged. The messages sent by AIS transponders are sent over VHF radio and have a range that is influenced by atmospheric conditions, the curvature of the Earth, and the altitude of both the transmitter and receiver. The effective range can be anything between about 50 and 100 km (Buhaug et al., 2009; Jalkanen et al., 2009). This means that methods are needed to establish realistic vessel activity profiles while vessels travel between areas that are within range of AIS receiver stations (Miola & Ciuffo, 2011).

Since 2010, satellites that specifically receive AIS messages have been in operation, making global AIS coverage a reality, which has significantly reduced the amount of time ships operate outside of network range (Endresen et al., 2008; Jalkanen et al., 2009; Ross et al., 2011; Smith et al., 2014). However, data archived by AIS satellites have their own associated challenges. One key issue is an increased likelihood that weaker signals broadcast by Class-B AIS transponders are less likely to be received due the signal degradation over the considerable distances to AIS satellites and over-crowding by more powerful Class-A AIS signals (Taylor-Branco, 2013). Nevertheless, the introduction of satellite-AIS (S-AIS) represents a significant improvement in the data available for the calculation of shipping emissions inventories.

For the production of the *Third IMO GHG Study 2014* (Smith et al., 2014), both satellite-AIS (S-AIS) and AIS data collected by coastal base-stations were used to create the most complete global AIS dataset ever utilized for emissions inventory calculation. This allowed emissions for the majority of commercial vessels (>100 GT and present in the IHS-Fairplay database) to be explicitly modelled from specific hourly activity data. This builds upon previous work incorporating satellite AIS data to understand shipping activity and energy use (Smith et al., 2013).

2.3.5 Proxy-activity-based methods

A number of studies use pre-existing or derived data on emissions per unit of an activity that is less directly related to vessel operation, such as emissions per tonne-kilometre or emissions per kilogram of fish caught. This approach has been used to determine emissions from cargo transport (Corbett, 2002; Corbett & Fischbeck, 2000; Georgakaki et al., 2005; Schrooten et al., 2009) and fishing (Tyedmers et al., 2005; Whall et al, 2002).

When used to determine emissions from cargo transport either pre-existing data on emissions per tonne-kilometre or tonne-mile of different types of cargo transported are used (Corbett, 2002), or vessel characteristics registers such as the IHS-Fairplay database are used to create hypothetical ‘average’ cargo vessels for carrying different types of cargo, for which emissions or fuel consumption per tonne-kilometre or tonne-mile are calculated (Corbett & Fischbeck, 2000; Georgakaki et al., 2005; Schrooten et al., 2009). Data on cargo movements and distances between ports are then used to determine the number of tonne-kilometres or tonne-miles travelled, from which fuel use and emissions are calculated.

Emissions inventories for fishing vessels using proxy-activity-based methods use pre-existing data on the amount of fuel used per unit of catch landed. Data on the quantity of catch landed from each fishing area are then used to calculate fuel use and emissions (Tyedmers et al., 2005; Whall et al, 2002). One advantage of this approach is that the activity-data used is usually geographically resolved, such as Food and Agricultural

Organisation (FAO) fisheries data on tonnages landed (FAO, 2018), which are presented by fishery area (Tyedmers et al., 2005); and Eurostat cargo movements data (Eurostat, 2018), which are presented as movements between a specific port and various Marine Coastal Areas (Georgakaki et al., 2005; Schrooten et al., 2009).

The advantage of using these data is that geographically resolved emissions inventories can be created using the actual activity data used rather than an auxiliary dataset. However, the resolution is limited to the resolution of the input data, and does not fully represent where emissions occur as actual vessel routes are not taken into account (Whall et al., 2002). This group of methods must also apply Tier 1 or Tier 2 emission factors given that specific load profiles can only be assumed.

2.3.6 Measurement-based inventories

A final category of methods that have been used for estimating the increase in atmospheric concentrations of pollutants as a result of shipping has been the use of air quality monitoring equipment. Using this category of methods involves measuring atmospheric concentrations of pollutants at a range of locations at varying distances from sites of shipping emissions such as ports and inland waterways and comparing them to background levels using pollution dispersion models. This allows the calculation of the contribution that shipping emissions make to overall pollution concentrations (Isakson et al., 2001, van der Zee et al., 2012).

Direct measurement within a priority area such as a port can also be used to determine whether air quality exceeds predefined levels such as national legal limits or World Health Organisation (WHO) recommended maximum pollutant concentrations (Dong et al., 2002). This category of methods tends only to be used in high priority locations such as close to ports (Dong et al., 2002; Isakson et al., 2001) and in cities where shipping activities occur in close proximity to residential areas (van der Zee et al., 2012). Outdoor air quality guidelines are published by the WHO with guidance on the maximum healthy concentrations of PM, ozone, NO_2 and SO_2 (WHO, 2005).

Other interesting methods that fall within this category employ the use of remote sensing equipment to quantify the environmental impact of shipping. So far only limited research has been carried out in this area, but it appears that satellite-mounted remote sensing equipment can be used to quantify the emissions of NO_X from shipping (Beirle et al., 2004) as well as the albedo altering effects of ship wakes (Gatebe et al., 2010).

Closer range methods such as Differential Optical Absorption Spectroscopy (DOAS) by devices mounted on airborne platforms have been pioneered by Berg et al. (2012) and have shown some promise in empirically measuring SO_2 and NO_2 emissions from ships. Beecken et al. (2014) have shown that airborne remote sensing measurements can reliably measure SO_2, NO_x and PM concentrations in ship exhaust plumes, which can be used to enforce compliance with fuel sulphur regulations. While the results from this experimental setup have a relatively high level of uncertainty, it has been used to calibrate the results of bottom-up activity-based methods (Jalkanen et al., 2014).

2.4 Emissions from small commercial, inland and recreational watercraft

Top-down fuel-based methods for the calculation of emissions inventories tend not to deal with emissions from small commercial, inland and recreational watercraft specifically. Although sales of fuel to these vessels should be included in aggregates, the data are not presented in such a way that they can be separated from other sectors (Buhaug et al., 2009). They are likely to be spread between international and domestic shipping as well as other sectors, such as agriculture for fishing vessels (Endresen et al., 2007). Therefore, top-down fuel-based methods are not suitable for the calculation of separate emissions inventories for small commercial watercraft.

As demonstrated by the various studies that have used bottom-up fuel-based approaches (Byrnes & Warnken, 2009; Curtis et al., 2006; De Meyer et al., 2008; Iribarren et al., 2010; Tyedmers, 2001), fuel use surveying is a viable method for estimating fuel use and emissions from small commercial watercraft. However, data collection is likely to involve significant effort each time the emissions inventory is to be calculated. It is also likely that survey results will only be obtainable for a proportion of the vessels in the fleet. Because of this, the methodology also requires data on the number, type and characteristics of small commercial watercraft so that the results of fuel use surveys can be scaled to the entire fleet. This will also give rise to additional uncertainty in the emissions inventory.

There are a handful of studies addressing fishing vessel emissions that use proxy-activity-based methods, based on average fuel use rates per unit of catch combined with data on the quantity of catch landed (Tyedmers et al., 2005; Whall et al, 2002). However, these methods are only applicable for vessels where some form of proxy activity data are available. When considering small commercial, inland and recreational vessels, it is unlikely that proxy activity data will be readily available for any vessel categories other than fishing.

Global, regional and national shipping emissions inventories compiled using activity-based methods also tend not to include small commercial, inland and recreational vessels. These omissions are as a result of the datasets used for the calculation of emissions inventories. Notably, the IHS-Fairplay and LMIU databases, which have been used extensively in emissions calculation, contain only limited information for vessels other than oceangoing commercial vessels of 100 GT and above (Endresen et al., 2007, 2008; Eyring et al., 2010; Schrooten et al., 2008). This is likely one of the main reasons that little research has been undertaken into the emissions of commercial watercraft under 100 GT, watercraft used exclusively on inland waterways and recreational vessels.

Emissions from small commercial, inland and recreational watercraft have been noted as a potentially significant omission from global and regional emissions inventories (Endresen et al., 2007, 2008), but little data exists to confirm this. The facts that have led to this suspicion are largely related to the number of fishing boats and workboats that are under 100 GT. It is thought that there are some 1.3 million fishing vessels worldwide, of which the majority are under 100 GT, representing approximately half of the global fishing fleet's installed engine power (Endresen et al., 2007, 2008). There are also around 3000 workboats and cargo vessels between 25 and 100 GT in size engaged in coastwise shipping around Denmark alone (Endresen et al., 2007, 2008).

Endresen et al. (2007) suggest that approximately 10% of fuel use and emissions associated with global shipping activities could be contributed by vessels under 100 GT. Conversely, the NTUA (2008) estimated that only 1% of fuel consumption and emissions from global shipping activities are caused by vessels less than 400 GT in size. However, this estimate is based on Lloyd's Register data, which is known to not contain the majority of vessels under 100 GT. This also seems to be at odds with previous findings, which have concluded that vessels between 100 and 500 GT in size are responsible for around 8% of global shipping emissions (Endresen et al., 2003). These smaller vessels are also likely to have lower quality engines than larger vessels, resulting in disproportionately high rates of pollution emissions (Endresen et al., 2007).

Small commercial and recreational watercraft have either been omitted entirely from emission inventories (Buhaug et al., 2009; Corbett & Köhler, 2003; Dalsøren et al., 2009; Endresen et al, 2003; Eyring et al., 2005, Wang et al., 2007; Corbett et al., 2010; Smith et al., 2014), or have been represented by adding an arbitrary amount to total emissions, such as a 10% uplift factor applied within 10 miles of coasts (Whall et al., 2007), or a 5% increase in emissions calculated using standard activity-based methods (Whall et al., 2010).

Very few studies have addressed this group of vessels directly. One notable study attempted to quantify emissions from vessels operating on the UK's inland waterways using a top-down activity-based method (Walker et al., 2011). However, many assumptions were made about vessel numbers, vessel characteristics and vessel activity profiles, so the results of this study should be viewed as highly uncertain. The study was also not conducted in such a way that commercial vessels under 100 GT could be distinguished from those of 100 GT and above. There are also a number of studies using bottom-up fuel-based methods that target specific types small commercial watercraft (Byrnes & Warnken, 2009; Curtis et al., 2006; De Meyer et al., 2008; Iribarren et al., 2010; Tyedmers, 2001) (see Section 2.3.2).

An AIS-based study that attempts to model emissions from small vessels directly is an emissions inventory for the Baltic Sea region produced by Jalkanen et al. (2014). In this work, all AIS records that cannot be associated with an IMO registered vessel are assumed to be produced by small vessels. These vessels are assigned engine characteristics typical of a tugboat and modelled accordingly.

The approach used by Jalkanen at al. (2014) for modelling the emissions of small commercial watercraft has some clear weaknesses. Firstly, given that small vessels are solely identified from the AIS data record, the fleet of small vessels modelled is limited to those with AIS devices. Many small commercial watercraft do not have AIS devices installed, as found in this research (see Chapter 6) and published in Coello et al. (2015). Secondly, all small vessels are assigned engine characteristics typical of a tugboat, which is likely to result to an overestimate of emissions from the vessels that are modelled due to the disproportionately large size of tugboat engines in comparison to other small vessels. However, bearing in mind these limitations, the results of the emissions inventory produced by Jalkanen et al. (2014) for the Baltic Sea region support for the estimate of around 10% of CO_2 emissions coming from small vessels made by Endresen et al. (2007).

Nevertheless, this work does highlight the potential for using AIS data for the production of emissions inventories for small commercial watercraft. To use AIS data effectively for this purpose, reasonable quality data are required on the vessel populations being modelled and their technical specifications. The installation of AIS devices is also only mandatory for ocean-going passenger vessels and other ocean-going vessels over 300 Gross Tonnes (GT). This means that only a subset of commercial, inland and recreational vessels use AIS devices voluntarily due to the safety benefits that they offer (MMO, 2013). Therefore, when using AIS data to produce emissions inventories for these vessels, the AIS data from vessels with AIS devices should be treated as a sample of vessel activity and scaled to the entire fleet in some way.

There are two key technical reasons for the absence of small commercial and recreational vessels from the majority of emissions inventories. These are 1) the absence of vessel databases containing vessel characteristics data for vessels under 100 GT, and 2) a paucity of activity data for these vessels. As AIS technology becomes increasingly affordable, a greater number of small commercial and recreational watercraft will produce this type of data. This is a valuable source of information for the inclusion of small commercial and recreational watercraft in shipping emissions inventories (Jalkanen et al., 2014).

2.5 Conclusions

A variety of methods for the calculation of shipping emissions inventories have been identified within the academic, government and industry literature. There is a general trend towards the use of activity-based approaches that are thought to be more reliable and also enable the geographic allocation of emissions and the use of higher tier technology-specific emissions factors. The most recent methods have made full use of AIS data for bottom-up activity-based emissions calculation given the advantages it offers for the production of high quality, temporally and spatially resolved emissions inventories and the application of Tier 3 technology-specific emissions factors.

Small commercial, inland and recreational watercraft have generally been omitted from major shipping emissions inventories due to a lack of vessel specification and activity data. This omission could be significant, with some researchers believing that this leaves around 10% of emissions from the shipping sector unaccounted for.

Given that a proportion of small commercial, inland and recreational watercraft use AIS devices, the AIS data that they produce can be used as a high quality sample of activity for vessels in these fleets. Therefore, an AIS-based approach that uses the AIS data produced by vessels with AIS devices as a sample of fleet activity is a potential solution for the lack of activity data for these vessels. The remainder of this thesis regards the use of AIS data to calculation emissions from small commercial watercraft. An AIS-based methodology that uses the available AIS data as a sample of fleet activity is developed and tested for a case study fleet of UK fishing vessels.

3 An AIS-based methodology to calculate emissions from small commercial vessels

The purpose of this chapter is to give a detailed description of the AIS-based emissions calculation methodology developed during this project. The methodology enables the calculation of emissions for small commercial watercraft using AIS data. Because small commercial watercraft fleets do not generally have 100% AIS device uptake, activity data are sampled for vessels from the AIS data that are available. Small commercial watercraft such as fishing vessels and tugs often perform pushing and pulling activities, so an approach for detecting and correcting engine loads when vessels are engaged in these activities is proposed. This chapter satisfies objective 2 of this project:

> *"To create a robust, repeatable and practical methodology for the calculation of atmospheric pollution caused by small commercial watercraft"*

3.1 Introduction

The majority of researchers in the field have concluded that activity-based methods are more reliable than fuel-based methods for the calculation of atmospheric emissions from shipping activities (Buhaug et al., 2009; Corbett & Köhler, 2003; Endresen et al., 2003; 2007; Eyring et al., 2005; Smith et al., 2014). This is largely due to uncertainties associated with fuel sales data due to underreporting and misallocation (Buhaug et al., 2009; Corbett & Köhler, 2003; Psaraftis & Kontovas, 2009; Schrooten et al., 2008) and issues of data completeness in the fuel-sales statistical records (Smith et al., 2014).

To produce activity-based emissions inventories, both technical information and activity data are required for the vessels that make up the fleet being analysed. The minimum technical data required are engine powers, types and fuels used and vessel design speed. Generally, the activity data required are the number of hours of engine operation and engine loads during operation (Buhaug et al., 2009; Corbett & Köhler, Dalsøren et al., 2007; 2009; Endresen et al., 2003; 2007; Eyring et al., 2005; Psaraftis & Kontovas, 2009; Smith et al., 2014; Whall et al., 2002, 2007, 2010).

Various sources of activity data are available. However, in recent years a new source of high-quality activity data has emerged with the introduction of Automatic Identification Systems (AIS). The data produced allows researchers the potential to reconstruct vessel activity using high-resolution temporally and spatially resolved vessel movement data (Jalkanen et al., 2009, 2012, 2014; MARIN, 2012; Olesen et al., 2009; Perez et al., 2009; Smith et al., 2014).

Given that AIS data contain highly accurate spatial and temporal information, AIS-based methods lend themselves to the production of detailed temporally and spatially resolved emissions inventories. These are preferable as they can be used as inputs to chemical transport models to assess the impacts of shipping upon air quality, human health and the environment (Corbett et al., 2007; Dalsøren et al., 2009; Jalkanen et al., 2014; Lauer et al., 2007; Winebrake et al., 2009).

Not all vessels transmit AIS data. Automatic Identification Systems (AIS) are a safety system that ocean-going passenger vessels and other ocean-going vessels over 300 Gross Tonnes (GT) are legally required to install and maintain. However, an increasing number of other vessels use AIS devices voluntarily as devices become more affordable (MMO, 2013; Jalkanen et al., 2014). Data broadcast by AIS devices include vessels' location and speed every few seconds, as well as additional vessel and trip data every few minutes (ExactEarth, 2014). AIS data are transmitted using very high frequency (VHF) radio and are received by other vessels, coastal receiver stations and an increasing number of satellites. The data received by coastal receiver stations and satellites are archived by government bodies such as the UK Maritime and Coastguard Agency (MCA) and private organisations such as *VesselTracker.org* and *MarineTraffic.com* (MarineTraffic.com, 2014; Vesseltracker, 2014; MMO, 2013).

Archived AIS data can be used to reconstruct vessel activity more accurately than less detailed activity data such as port arrivals and departures. Significantly, the use of AIS data allows for dynamic, rather than average, speed to be used in load calculation, reducing uncertainty. Recent emissions inventories, including the Third IMO GHG Study 2014 (Smith et al., 2014), have utilised AIS data due to the superior accuracy and high resolution of emissions inventory that it makes possible. However, using AIS data is associated with a significant technical effort in creating the software to process it (Jalkanen et al 2009; 2012; 2014; Smith et al., 2014).

All of the methods for using AIS data for true vessel-level emissions calculation have relied on directly matching each vessel to their activity track (the chronologically ordered AIS data generated by the vessel). Jalkanen et al. (2009; 2012; 2014), MARIN (2012) and Perez et al. (2009) highlight the difficulties associated with accurately matching vessels to AIS data due to data gaps and inconsistencies within the various datasets used. Smith et al. (2014) remedied this by associating any vessels for which AIS data were not identifiable to a track created by a similar vessel. However, the methodology relies on being able to match vessels one-to-one with their AIS data in the majority of cases and having one-to-one matching with AIS data of vessels sharing similar characteristics to those that cannot be matched to use as a basis for sampling.

In the case of small commercial vessels, making a direct match becomes increasingly difficult because less comprehensive data records are maintained, and the data required to make a matching are often absent. Notably, commercial vessels under 100 GT in size are generally not IMO registered and, therefore, do not have IMO numbers. This is a key piece of data used to match vessels with AIS tracks in other AIS-based shipping emissions inventory research. Where very few or no vessels can be directly matched to AIS data, an alternative method for sampling activity information from the AIS data is required.

An additional challenge, acknowledged by De Meyer et al. (2008) is associated with engine load calculation for vessels such as tugs, dredgers and trawlers, where, in certain operating modes such as towing and pushing operations, the engine load calculation formulae typically used in activity-based methods will significantly underestimate engine load due to the vessel running at high engine load but travelling at a slow speed.

This chapter presents an activity-based methodology for producing spatially and temporally resolved emissions inventories for small commercial vessels using Automatic Identification

Systems (AIS) data. The methodology makes significant contributions in dealing with fleets where one-to-one matching of vessels and AIS data is not possible using a sampling approach to enable emissions calculation and mapping. A methodology has also been developed that enables the assignment of appropriate engine loads for vessels such as tugs, dredgers and trawlers when engaged in pushing or towing operations. An early version of the methodology was used to produce an emissions inventory for the UK fishing fleet which was published as an academic journal paper (Coello et al., 2015).

The source code for the software developed to implement the methodology described in this chapter is provided in the accompanying material provided on the USB key submitted with this thesis. The case study datasets are also provided so that the model can be run and results can be repeated if desired.

3.1.1 AIS devices and data

There are two classes of AIS device. Class-A devices are more powerful and are reserved for use by vessels for which the use of AIS technology is mandatory. For voluntary AIS users there are less expensive but also less powerful Class-B devices available (Vesseltracker, 2014), which are aimed at smaller vessels such as private recreational and fishing vessels (MMO, 2013).

The messages broadcast by AIS transponders comprise two types; position reports (e.g. Table 3.1) and voyage data. Class-A AIS transponders broadcast position reports every 2 to 10 seconds while a vessel is moving and every 3 minutes whilst stopped. Additional vessel and voyage data are broadcast every 6 minutes (ExactEarth, 2014). Class-B transponders transmit the same data but do so less frequently when moving, with messages broadcast every 30 seconds (Danish Maritime Authority, 2014).

Each position report contains the information shown in Table 3.1. Broadcasts are identified by a Marine Mobile Service Identity (*MMSI*) number, which is a unique identifier of a vessel for use with marine mobile communications equipment. The *Type* is one of a list of 132 identity numbers representing different types of ship, search and rescue aircraft and helicopters or navigational aids (e.g. buoys) that broadcast AIS messages. *Speed*, *longitude*, *latitude*, *course*, and *heading* are automatically calculated by a Global Positioning System (GPS) unit and gyro-compass integrated into the AIS transponder.

The *status*, an ID number which relates to a vessel activity, e.g. *underway* (0) or *moored* (1), is manually set by the operator. The *timestamp* represents the time, in Coordinated

Universal Time (UTC), that the AIS message was received by the AIS network operator (MMO, 2013). Whilst AIS transponders can transmit data as frequently as once every two seconds, the timestamp has been expressed to the nearest minute as the network operator considers network latencies to render a higher level of temporal resolution redundant (Memos, 2013).

In addition to these dynamic data, the vessel's name, IMO Number (if applicable), call sign, length, destination and estimated time of arrival (ETA) are reported in separate messages, which are sent less frequently and are also identified by MMSI number (ExactEarth, 2014).

Table 3.1. AIS data structure and example data. The data within this table is a fabrication, intended as an example only.

MMSI[a]	Type	Status	Speed (knots)	Longitude (°)	Latitude (°)	Course (°)	Heading (°)	Timestamp[b]
123456789	30	0	3	6.103367	53.45756	323	317	2012-05-14 02:16:00
234567890	22	1	0	-1.286293	45.60667	276	106	2012-05-14 02:16:00
345678901	57	5	0	6.045917	53.50425	263	264	2012-05-14 02:17:00
456789012	44	7	25	4.202433	57.71735	319	308	2012-05-14 02:17:00

a) Marine Mobile Service Identity

b) Timestamps in Coordinates Universal Time (UTC), a time-zone independent measure of time.

3.2 AIS data analysis

3.2.1 Materials and methods

This chapter concerns the development of a methodology and associated software to process AIS data to produce atmospheric emissions inventories for the activities of small commercial vessel. Fishing vessels make up an important component of the small commercial vessel fleet. It was also found that European Commission maintain the Community Fleet Register database of fishing vessels, which contains some of the information required as inputs to an activity-base emissions calculation methodology (EC, 2013a). Importantly, the power of main and auxiliary engines are listed in this register.

A sample of AIS data was obtained for fishing vessels in the area bounded by latitudes 40˚N and 65˚N and longitudes 20˚W and 12˚E between 9th May 2012 and 15th May 2013 via the *MarineTraffic.com* researcher network. The combination of these datasets and data available in the published literature was sufficient to enable the calculation of an emissions inventory for the UK fishing fleet over the period of a year. Therefore, UK fishing fleet was taken as the case study fleet of small commercial vessels for the development of this methodology.

The AIS data provided by *MarineTraffic.com* comprised a total of 55,465,377 rows of AIS position messages associated with 5187 unique MMSI numbers. One can assume that each of these MMSI numbers represented a unique vessel. Each row of data represents a timestamped geographic position and speed. Each of these will be referred to as an 'AIS data point'.

Analysis of the AIS data was performed and AIS technologies were considered to identify potential data quality issues that would need to be addressed during the development of a robust approach for processing AIS data to produce emissions inventories. Frequency counts of the data values associated with each AIS data point were calculated. Status IDs were analysed to determine whether they could be used to reliably determine a vessel's activity, such as being underway or at anchor. Speed was analysed to gauge how realistic the speed values in the AIS data were. Time intervals between chronologically consecutive AIS data points associated with each individual MMSI number were analysed by sorting data in ascending order of timestamp and calculating the difference in timestamp between adjacent AIS data points. The results of these analyses are presented below.

3.2.2 Results of AIS data analysis

Analysis of the time intervals between chronologically consecutive AIS points showed 51.26% of intervals to be less than 5 minutes long. A further 43.31% of were 5 to 30 minutes long and 3.75% were 30 to 60 minutes long (Figure 3.1). The remaining 1.68% of time intervals was made up of times of 1 hour or more (Figure 3.2).

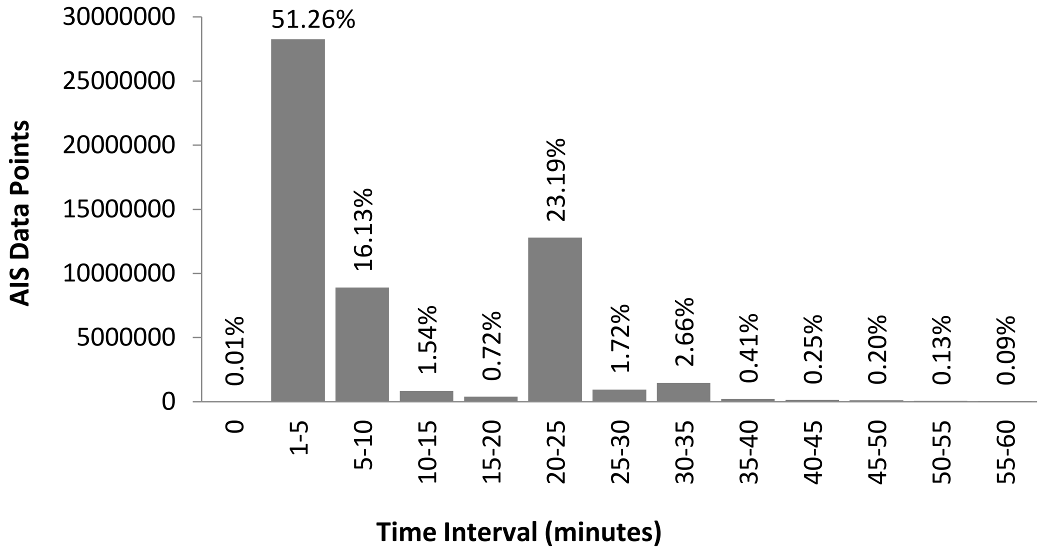

Figure 3.1. Frequency distribution of time intervals between chronologically consecutive data points in the AIS data used in model development, intervals from 0 to 60 minutes.

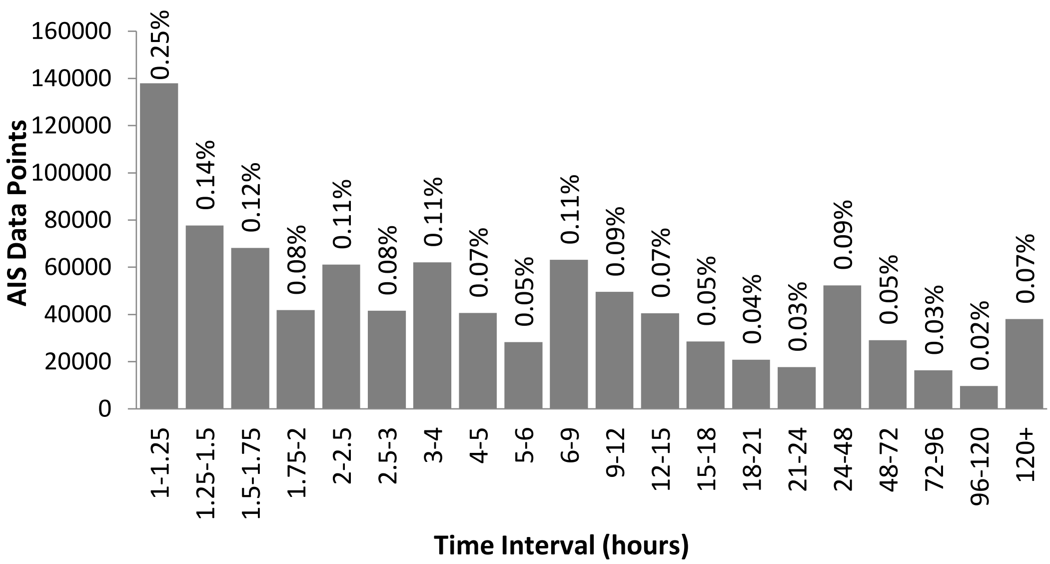

Figure 3.2. Frequency distribution of time intervals between chronologically consecutive data points in the AIS data used in model development, intervals from 1 hour upwards.

A significant proportion (26.26%) of AIS data points recorded a speed of 0 knots. Speeds between 0.1 and 14.9 knots were reported by a further 73.52% of AIS data points (Figure 3). Just 0.21% of AIS data points recording values of 15.0 knots or more with 0.06% of data points showing a speed of 102.1 knots, the maximum AIS speed value (Figure 4).

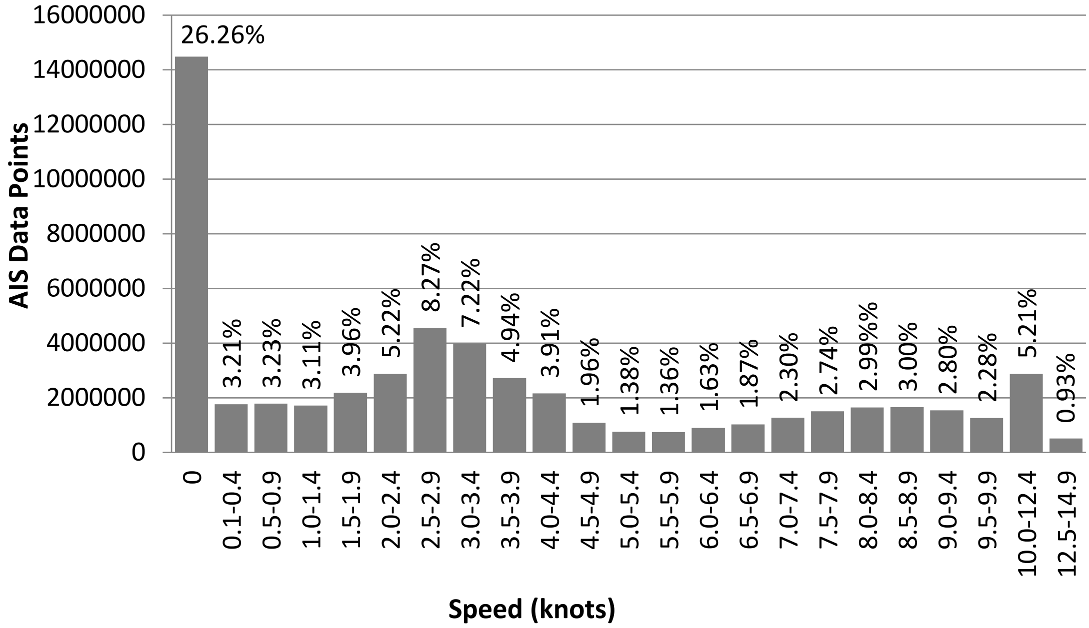

Figure 3.3. Frequency distribution of speeds reported in the AIS data used in model development. Speeds from 0 to 14.9 knots.

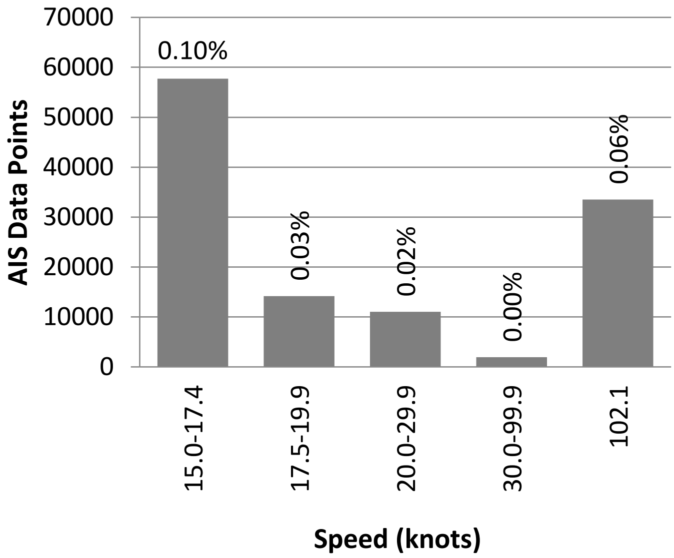

Figure 3.4. Frequency distribution of speeds reported in the AIS data used in model development. Speeds from 15.0 to 102.1 knots.

Analysis of AIS *status* showed that 31.0% of AIS data points were reported as 'engaged in fishing', 23.7% as 'underway', 22.1% had the default value set and 16.2% had values that are not currently supposed to be in use. Only 4.2% had statuses of 'at anchor' or 'moored'.

3.2.3 Discussion of AIS data analysis and AIS data quality issues

Analysis of data and consideration of AIS technologies highlighted a number of potential data quality issues that must be considered when working with AIS data (Table 3.2). Failure to properly account for these could lead to significant errors in the resulting emissions inventories.

Table 3.2. Data quality issues associated with AIS data.

Issue	**Cause**	**Impact**
Large time intervals between archived AIS data points belonging to a track	• AIS transponder malfunction • Vessels operating outside of AIS network range • AIS base-station malfunction or overloading • Operators switching off AIS devices or cutting power supply	Uncertainty of vessel's actual speed
Unrealistically high speeds recorded in AIS data	• Malfunction of GPS device integrated with AIS transponder • Multiple vessels using the same MMSI number	
More than one AIS data point for a given MMSI number sharing a single timestamp	• Some AIS network operators round timestamps to the nearest minute	Uncertainty of route taken between points
Inaccurate status data	• These are user input and, therefore, are prone to human error, negligence and deceit.	Uncertainty of vessel identity, characteristics and route
Inaccurate static data such as name, IMO number, call sign, length, destination		

and estimated time of arrival		

The availability of AIS data provides much more information than was previously available to researchers to reconstruct shipping activity profiles. However, each AIS data point only provides an instantaneous snapshot. A vessel's activities between archived AIS data points are unknown and must be inferred from the data available. Therefore, where the AIS data points are infrequent or irregular, the level of uncertainty in the inferred activity profile increases.

A small but not insignificant number of long time intervals were found in the AIS data, some of 24 hours or more (Figure 3.2). Because of their length these will make up a disproportionately large proportion of an AIS track's total duration. Large time intervals between AIS data points are problematic when using AIS data in emissions modelling if the distance and time interval between points are used to calculate speed. The likelihood that a ship travelled the shortest distance (a great circle arc) between two points decreases as the time interval increases. Speed calculated in this way is, therefore, uncertain and likely to be an underestimate. If interpolating or averaging the speeds recorded in AIS messages, the likelihood that the speeds of two AIS data points are representative of the speed between them reduces as the time interval increases.

There are several causes of large time-intervals in a continuous AIS data record. AIS data are only archived when they are received by AIS base-stations (Buhaug et al., 2009; MMO, 2013). Base-stations are shore-, buoy- or satellite-mounted and have a range that is determined by signal disruption and signal strength. For terrestrial base-stations the range is around 90 km (Jalkanen et al., 2009). Disruption is caused by the curvature of the Earth, adverse atmospheric conditions and other physical obstructions (Buhaug et al., 2009; MMO, 2013). Signal strength varies with the power of AIS transponder used and degrades with distance from the source. Due to these factors, AIS messages broadcast by vessels operating far from base-stations are unlikely to be received and archived. This effect is compounded when vessels are fitted with Class-B AIS transponders that broadcast a weaker signal (Taylor-Branco, 2013).

The significance of the errors caused by large time intervals depends on the type of journey. Figure 3.5 helps to visualise the errors caused by vessels operating outside of AIS network coverage. Journey A is entirely within AIS network range and is unlikely to have significant data-gaps. Journey B leaves and re-enters AIS network coverage; however, calculating an average speed for the direct route between the points of exit and re-entry would result in a reasonable estimate of vessel speed with only minor errors. Journey C, however, is an example where leaving network coverage would lead to a significant underestimate of the distance travelled and, therefore, speed and emissions.

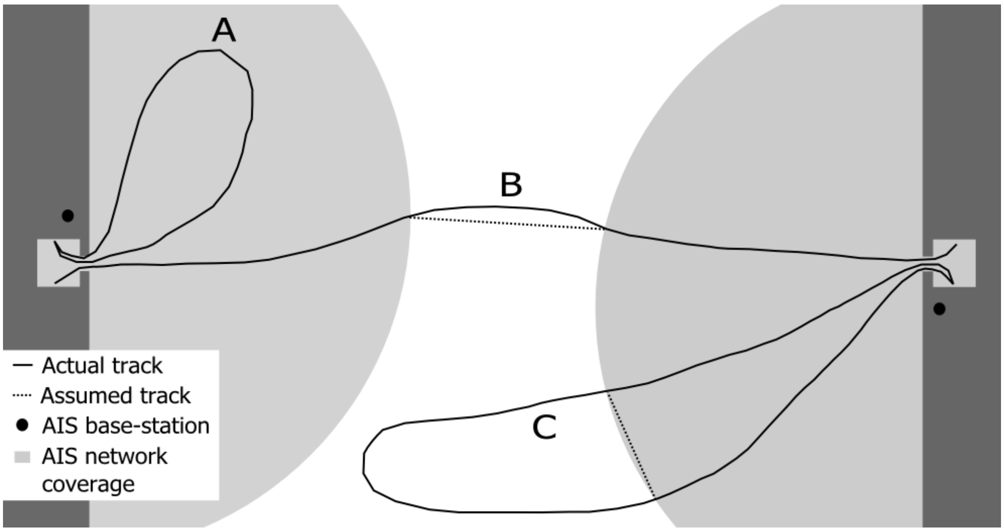

Figure 3.5. Creating track segment groups of a minimum specified length from AIS data. Example of a minimum track segment group duration of 20 minutes.

AIS transponders or receivers may malfunction, or base-stations may become overcrowded with AIS messages due to heavy marine traffic. In these situations, the AIS messages with stronger signal strength are more likely to be recorded, meaning that messages from more distant vessels and vessels fitted with less powerful Class-B AIS transponders are less likely to be archived (Taylor-Branco, 2013).

It was also found that multiple AIS data points in a single track can share the same timestamp and, therefore, have a time interval of zero (Figure 3.1). *MarineTraffic.com*, the AIS data supplier, explained that this was because timestamps are recorded to the nearest minute. This is due to network latencies that renders the use of more accurate timestamps meaningless (Memos, 2013). If using time intervals between AIS data points to calculate speed, this needs to be addressed as dividing by zero will result in errors. For other time intervals the uncertainty associated with the speed should be addressed.

There are also issues with using AIS data for certain types of vessel. For certain fleets, such as small commercial and recreational vessels, AIS transponders are not mandatory and therefore only a proportion of these fleets have AIS transponders fitted. This means that one-to-one matching of vessels to the AIS data they produce is not sufficient to calculate an emissions inventory for the entire fleet. The AIS data that is available can, however, be used as a sample of fleet activity in order to estimate atmospheric pollution emissions. In order to do this, appropriate sampling methods must be developed.

Activity-based emissions models rely heavily on estimates of engine load from vessel speed. A small proportion of the AIS data had unrealistically high speeds. The reasons for this are unknown but could be the result of errors produced by the GPS units integrated with AIS transponders. Using these speeds in engine load calculation will cause errors.

Certain types of vessels such as tugs, dredgers, trawlers and icebreakers engage in pushing and towing operations where the use of speed to calculate engine load is not viable. For fishing activities, there is a corresponding AIS status type which could theoretically be used to indicate that an alternative engine load calculation method should be used if accurate. However, an unrealistically high proportion of the AIS data was found to be flagged as 'engaged in fishing' and many data points had the default or undefined status values. This is probably the result of AIS device users failing to update AIS status. What defines a vessel as being engaged in fishing is also debatable as the operator could legitimately regard moving to, from and between fisheries as being engaged in fishing. Given these uncertainties and the apparently poor quality of the AIS status information, a decision was made not to use status type in emissions calculation.

A final consideration is that AIS and other activity data are useful as a source of information about vessels movements and can be used to model main engine load. Information about the vessel's operations and trip phase can also be estimated, which allows selection of appropriate auxiliary engine loads. When a vessel is stopped, however, assumptions must be made about their main and auxiliary engine operation as the activity data cannot indicate anything beyond the fact that the vessel is stationary.

3.3 AIS-based emissions computation methodology

A new methodology and software tool has been created to enable the calculation of emissions to the atmosphere caused by small commercial watercraft. The methodology builds upon previous bottom-up activity-based approaches that make use of AIS data with some adaptations that were necessary to suit the specific challenges of modelling small commercial vessels. The software developed addresses a number of AIS data quality issues that are expected to occur to varying degrees for any AIS dataset (Section 3.2.3). In addition to this, a new activity sampling technique is presented that allows calculation of emissions for vessels that cannot be directly matched to AIS data provided that a reasonable sample of AIS data is available for some vessels within the fleet.

The software was developed in the Java programming language. Java was chosen as the language for the project because it is fast, mature, actively developed and supported, well tested, freely available, has a large user community and many open source and freely available libraries and developer tools. It is a strongly typed, compiled language that encourages good object orientated software development practices and makes debugging and testing of large applications easier for the developer than some other popular programming languages such as Python. It also has good support for multithreaded computation, meaning that it could be used to create software that could perform the calculations rapidly enough for many model runs to be carried out. Java is also designed for portability, and can be run on any commonly used operating system and hardware.

At the core of the methodology is an adaptation of the Tier 3 emissions calculation methodology from the *EMEP/EEA air pollutant emission inventory guidebook 2016* (Trozzi et al., 2016), described in Equations 3.1 and 3.2. The original methodology uses an estimate of the total time spent in different trip phases (p). Emissions are calculated for each trip phase and summed to give trip emissions. In the adapted version of the formula presented in this thesis (Eq. 3.3), emissions are calculated for the activity between each chronologically consecutive pair of AIS data points, with engine load estimated from speed. Fuel consumption rates (SFC) and emission factors (EF) from Trozzi et al. (2016) are selected based on engine type and trip phase. Emissions calculation is carried out using engine powers, types and fuels from a vessel characteristics database. The vessel characteristics database that serves as one of the key inputs to the modelling software requires data that should be readily available in any pre-existing vessel characteristics databases. Where a vessel’s engine and fuel type is unknown, numerous engine and fuel type combinations can be assigned with accompanying probabilities for use in emissions calculation (Eq. 3.4).

$$E_{Trip,i,j,m} = \sum_p \left[T_p \sum_e \left(P_e * LF_e * EF_{e,i,j,m,p}\right)\right] \quad \text{Eq. 3.1}$$

$$E_{Trip,i,j,m} = \sum_p \left[T_p \sum_e \left(P_e * LF_e * SFC_{e,j,m,p} * EF_{e,i,j,m,p}\right)\right] \quad \text{Eq. 3.2}$$

where:

E_{Trip} = emission of a pollutant over a complete trip (kg),

EF = emission factor (kg/tonne or g/kWh), e.g. from Trozzi et al. (2016),

LF = engine load factor (%),

P = engine nominal power (kW),

SFC = specific fuel consumption rate (g/kWh),

T = time (hours),

e = engine category (main, auxiliary),

i = pollutant (CO_2, NO_X, SO_2, NMVOC, CO, PM),

j = engine type (slow-, medium-, and high-speed diesel, gas turbine and steam turbine),

m = fuel type (bunker fuel oil, marine diesel oil/marine gas oil, gasoline),

p = the different phase of trip (cruising, hotelling, manoeuvring).

$$E_{e,i,j,m} = \sum_{ts} T_{ts} \sum_e \left(P_e * LF_e * SFOC_{e,j,m,p} * EF_{e,i,j,m,p}\right) \quad \text{Eq. 3.3}$$

where:

ts = track segment.

$$E_{e,i,j,m} = \sum_{ts} T_{ts} \sum_e \sum_{j,m} C_{j,m} * \left(P_e * LF_e * SFOC_{e,j,m,p} * EF_{e,i,j,m,p}\right) \quad \text{Eq. 3.4}$$

where:

C = the probability that a given combination of engine type (j) and fuel (m) are used.

3.3.1 Data requirements

Five datasets are required for the emissions calculation as well as three additional settings files. The main datasets are AIS data, vessel characteristics data, emissions factors, port locations and an additional vessel database containing information about each vessel in the AIS dataset (compiled from voyage data AIS messages, see Section 3.1.1). The settings files are *AIS ship type profiles*, *vessel type profiles* and *engine load override rules*. These contain settings used during data processing and emissions calculation.

The MMSI number is used for matching vessels to AIS data. Ideally, AIS data for the entire fleet for which an emissions inventory is to be calculated would be used during emissions calculation and directly matched to vessel characteristics using MMSI number. However, if AIS data are only available for a sample of vessels due to lack of access, cost, or because some of the vessels in question do not have AIS devices installed, emissions can be calculated using the available AIS data as a sample of vessel activity.

In order for AIS data to be used as a sample without producing significant errors, the AIS data sampling approach must be carefully considered. This is briefly addressed in Section 3.3.2 below and given a detailed treatment in Chapter 4. Of course, activity sampling is inherently less accurate than directly matching vessels to their specific AIS tracks. Therefore, it is important that the uncertainty of the emissions inventory produced is calculated and that an attempt is made to quantify the impact of activity sampling. This is addressed in Chapter 5.

The vessel characteristics data required includes the power of main and auxiliary engines, and, ideally, the engine and fuel types used. If engine and fuel type data are unavailable for a vessel, fleet level statistics, such those in the *EMEP/EEA air pollutant emission inventory guidebook 2016* (Trozzi et al., 2016) (Table 3.3), can be used as probabilities that a vessel uses certain engine and fuel types. It is worth noting that bunker fuel oil (BFO) is a fuel used exclusively by larger vessels with large engines, while marine diesel oil (MDO) and marine gas oil (MGO) are used in all sizes of vessels. This explains why the majority of fishing vessels use MDO/MGO.

Table 3.3. Percentage of installed main engine power by engine type/fuel class (2010 fishing fleet) (after Trozzi et al., 2016).

SSD MDO /MGO	SSD BFO	MSD MDO /MGO	MSD BFO	HSD MDO /MGO	HSD BFO	GT MDO /MGO	GT BFO	ST MDO /MGO	ST BFO

0.00	0.00	84.42	3.82	11.76	0.00	0.00	0.00	0.00	0.00

SSD – Slow Speed Diesel, MSD – Medium Speed Diesel, HSD – High Speed Diesel, GT – Gas Turbine, ST – Steam Turbine, MDO – Marine Diesel Oil, MGO – Marine Gas Oil, BFO – Bunker Fuel Oil

Other vessel characteristics such as MMSI number, International Maritime Organisation (IMO) number, Gross Tonnage (GT), length and design speed should be included where possible. Vessel characteristics such as GT and length, as well as engine characteristics and *vessel type profiles* can be used to categorise vessels during emissions aggregation.

Any number of *engine load override rules* can be associated with a *vessel type profile*. *Engine load override rules* are introduced to correct engine load estimates for special types of vessel operation such as trawling, dredging, towing and pushing, for which the normal moving engine load calculation formula outlined in Section 3.3.3 does not produce a realistic estimate of engine load. An *engine load override rule* is a speed range for which a special engine load should be applied. A minimum and maximum duration of activities within the specified speed range can also be set to refine the identification of special operating conditions. For example, an *engine load override rule* for a fishing trawler may state that if a vessel is operating between 2.5 and 3.2 knots for at least two hours, apply an engine load of 75% (i.e. assume the vessel is trawling) (Table 3.4).

The engine load override rules used for the case study fleet of UK fishing vessels are listed in Table 3.4. Engine load override rules for fishing vessels using trawling and dredging gear were kindly recommended by Seafish, the industry body representing the UK seafood industry, through email correspondence with the author (Montgomerie, 2013).

A database of port location data was used to identify when vessels stop or operate in the area of ports. The port database contains port name, latitude, longitude and country. This database was compiled by overlaying the stops detected in the AIS data record onto aerial and satellite imagery from GoogleEarth™ and visually inspecting the groupings near shore to identify ports. This approach was useful as it identified all ports of relevance for the particular AIS dataset used. It also enabled the detection of many small ports that did not feature on any publicly available lists of ports found. The port dataset created for this research is available in the CaseStudyData directory of the accompanying electronic material.

Table 3.4. Engine load override rules developed with information provided by Seafish (after Montgomerie, 2013).

Trawler type	**Rule**	**Engine load to apply**
Trawler (<224 kW)	Classify as trawling if operating at 2.0-2.8 knots for at least 2 hours whilst not in port	75%
Trawler (224-597 kW)	Classify as trawling if operating at 2.5-3.2 knots for at least 2 hours whilst not in port	75%
Trawler (≥597 kW)	Classify as trawling if operating at 3.5-4.2 knots for at least 2 hours whilst not in port	75%
Dredger (<224 kW)	Classify as dredging if operating at 2.0-2.8 knots for at least 20 minutes whilst not in port	75%
Dredger (224-597 kW)	Classify as dredging if operating at 2.5-3.2 knots for at least 20 minutes whilst not in port	75%
Dredger (≥597 kW)	Classify as dredging if operating at 3.5-4.2 knots for at least 20 minutes whilst not in port	75%

With a port database such as this, it is possible to identify when AIS tracks visit ports by analysing the proximity of stops to port locations. The country of ports visited is used to identify when vessels stop at different countries. This data could be used to allocate emissions to different countries when dealing with international shipping activities. For example, the emissions generated on a journey could be allocated entirely to the origin or destination country, or shared between the two. However, given that the case study fleet is a fishing fleet, which is considered a domestic activity, all emissions were allocated to the UK. The country of visited ports can also be used to identify the AIS tracks that are associated with a country. This is discussed in more detail in Chapter 4.

3.3.2 AIS track sampling

MarineTraffic.com (2013), the AIS data provider for this project, maintain a publicly available website through which some basic vessel information broadcast in static AIS data messages are accessible. These data are searchable by MMSI number include vessel names. Initially, an attempt was made to match AIS tracks with the vessels in the vessel characteristics database using these names. However, it was found that only a very small proportion of vessels could be confidently matched by name and so the approach was abandoned.

As AIS data include a ship type, sampling AIS data generated by vessels of an appropriate type is straightforward. The static AIS data also include vessel length. Initially it was considered that vessel length, taken as an indicator of vessel size, could correlate with vessel activity and, therefore would be useful in activity sampling. However, further investigation, presented in Section 4.4 found that length was not a good predictor of vessel activity. Further information can be determined from summary statistics produced during AIS pre-processing that can be used to further refine the sample selected.

The AIS data can be analysed to show stops at ports and, on this basis, AIS tracks can be related to countries. Using this information, it is possible to filter for AIS tracks that are related to a specific countries. This is investigated thoroughly in Section 4.5. In addition, the number of AIS data points, percentage of a track that is in a state of error and the overall duration of the track (time between first and last AIS data points) can also be used to filter tracks during sampling.

For each model run, the number of AIS tracks to sample for each vessel is specified. The sampling approach developed first filters for AIS tracks with the appropriate vessel type and a minimum percentage of stops at the country or countries included in the study. The returned tracks are then filtered to leave only tracks with a specified maximum percentage of error and a minimum duration. If more than the required number of tracks is found, the desired number of tracks is randomly selected. A thorough investigation into track sampling is presented in Chapter 4.

3.3.3 Calculating moving engine load

In the *IMO Second GHG Study 2009*, engine load is calculated as the cube of a vessel's instantaneous speed (V_i) relative to its design speed (V_d), assuming a vessel's design speed is reached at 90% of an engine's maximum continuous rating (MCR) (Eq. 2.3) (Buhaug et al., 2009).

This method of load calculation is relatively reliable for high engine loads, but does not give an adequate estimation of low engine loads as an engine that is running will consume fuel even if the vessel is stationary due to a baseline idling engine load. An approach that incorporates this is used by MARIN (2012) (Eq. 3.5), scaling engine load between a minimum value and 100%. MARIN (2012) suggest an idling engine load of 10%, yet propose a formula that does not allow engine loads below 16.7% (0.2/1.2). Equation 3.5 also works on the assumption that 100% engine load will be reached at design speed, which is contrary to the method proposed by Buhaug et al. (2009) and later used in Smith et al. (2014).

What is needed is an engine load calculation formula that approximates engine load from vessel relative speed and correctly scales between a minimum (idling) engine load and a maximum engine load when the vessel reaches design speed (1 – sea margin). Equation 3.6 was devised for use in this research to meet these requirements. Engine load is scaled between a specified minimum and maximum load using relative speed to approximate engine load using an cubic power relationship. Trozzi et al. (2016) suggest a main engine load of 20% while vessels are hotelling with their main engines running. This could also be applied as an idling engine load. A 10% sea margin is used in Buhaug et al. (2009), resulting in a maximum engine load of 90% at design speed. On this basis, L_{min} could be set to 20% and L_{max} could be set to 10%. An investigation of the sensitivity of model outputs to changes in the parameters of the engine load calculation formula is undertaken in Chapter 5, the results of which are available in Section 5.4.1. Figure 3.6 is included to help visualize the differences between the three formulae for approximating engine load from vessel relative speed.

Given that the cubic power law for relating engine load to vessel speed is only a rough approximation, engine load may be calculated more accurately through prediction of required power at a particular speed in calm water and in waves, provided that sufficient vessel parameters are known (Dedes, 2013). With sufficient data on vessel parameters and waves, the methodology presented in this thesis could be adapted to use an engine load calculation methodology such as this with a resulting reduction in error and uncertainty of results.

$$LF = \frac{\left(\frac{V_i}{V_d}\right)^3 + 0.2}{1.2}$$ Eq. 3.5

$$LF = L_{max} * \left(\frac{\left(\frac{V_i}{V_d}\right)^3 + \left(\frac{L_{min}}{L_{max} - L_{min}}\right)}{1 + \left(\frac{L_{min}}{L_{max} - L_{min}}\right)} \right)$$ Eq. 3.6

where:

LF = Load factor,

V_i = Instantaneous speed of vessel (km h^{-1}),

V_d = Design speed of vessel (km h^{-1}),

L_{min} = Minimum engine load while main engine in operation,

L_{max} = Maximum engine load while main engine in operation.

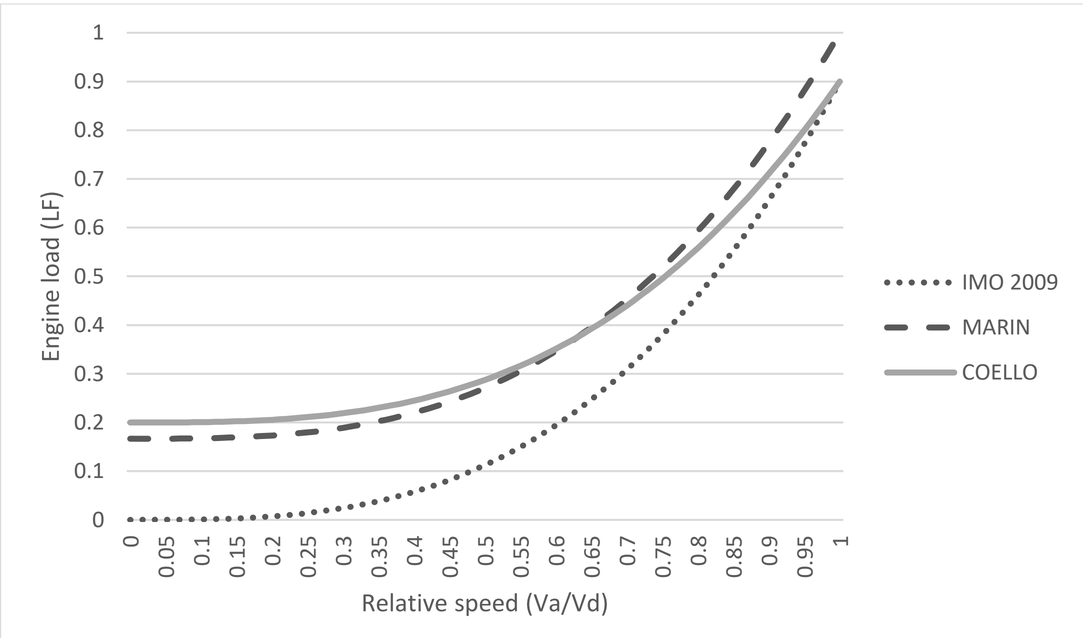

Figure 3.6. A comparison of three engine load approximation formulae. IMO 2009 (Eq. 2.3), MARIN (Eq. 3.5) and the formula used in this research (COELLO) (Eq. 3.6).

3.3.4 Process overview

The processing of AIS data and emissions calculation is carried out in three major phases. These phases are outlined in Figure 3.7. During phase 1, the AIS data points associated with each distinct MMSI number are grouped and chronologically ordered to produce an 'AIS track'. The great circle arcs, called 'track segments', that connect chronologically consecutive AIS data points within tracks are created and their distance, duration and speed are calculated. Indicators of poor data quality are identified and classified as errors. Potentially applicable *engine load override rules* are identified based on track segments or groups of track segments that meet the speed and duration criteria. Port visits are identified when stops are registered in the proximity of ports within the port location database and the track segments between port visits are grouped into journeys. Phase 1 is described in detail in Section 3.3.5.

Phase 2 involves matching vessel characteristics data to AIS activity data to calculate main and auxiliary engine running times and load factors. If the vessel's MMSI number is known and AIS data for that MMSI number are available, the vessel's specific AIS track can be used. Otherwise, a group of AIS tracks are sampled to represent the vessel's activity. Based on settings in the *vessel type profile* for each vessel, main and auxiliary engine loads are calculated from vessel speed when vessels are moving. When stopped, main and auxiliary engine running times and load factors are calculated based on assumptions. Any *engine load override rules* associated with the *vessel type profile* are applied to applicable sections of each AIS track. Mean main and auxiliary engine loads for in-port and not-in-port track segments are applied to track segments with errors. Phase 2 is described in Section 3.3.6.

In Phase 3, the main and auxiliary engine running times and load factors generated during the previous phase are used to calculate fuel use and atmospheric emissions. Appropriate emission factors are selected for each vessel's main and auxiliary engine and fuel type. Emissions are calculated using the main and auxiliary engine loads and duration of each track segment along with vessel characteristics data and emission factors. Emissions are allocated to time windows as well as being added to any emissions maps specified. Where a sample of multiple AIS tracks is used to represent vessel activity, the mean fuel use and emissions within each time window are calculated. Vessel emissions data can then be aggregated for groups of vessels and specific time ranges. Phase 3 is described in detail in Section 3.3.7. To help explain the emissions calculation procedure, a narrative example is given of calculating emissions for a fictional vessel in Section 3.3.8.

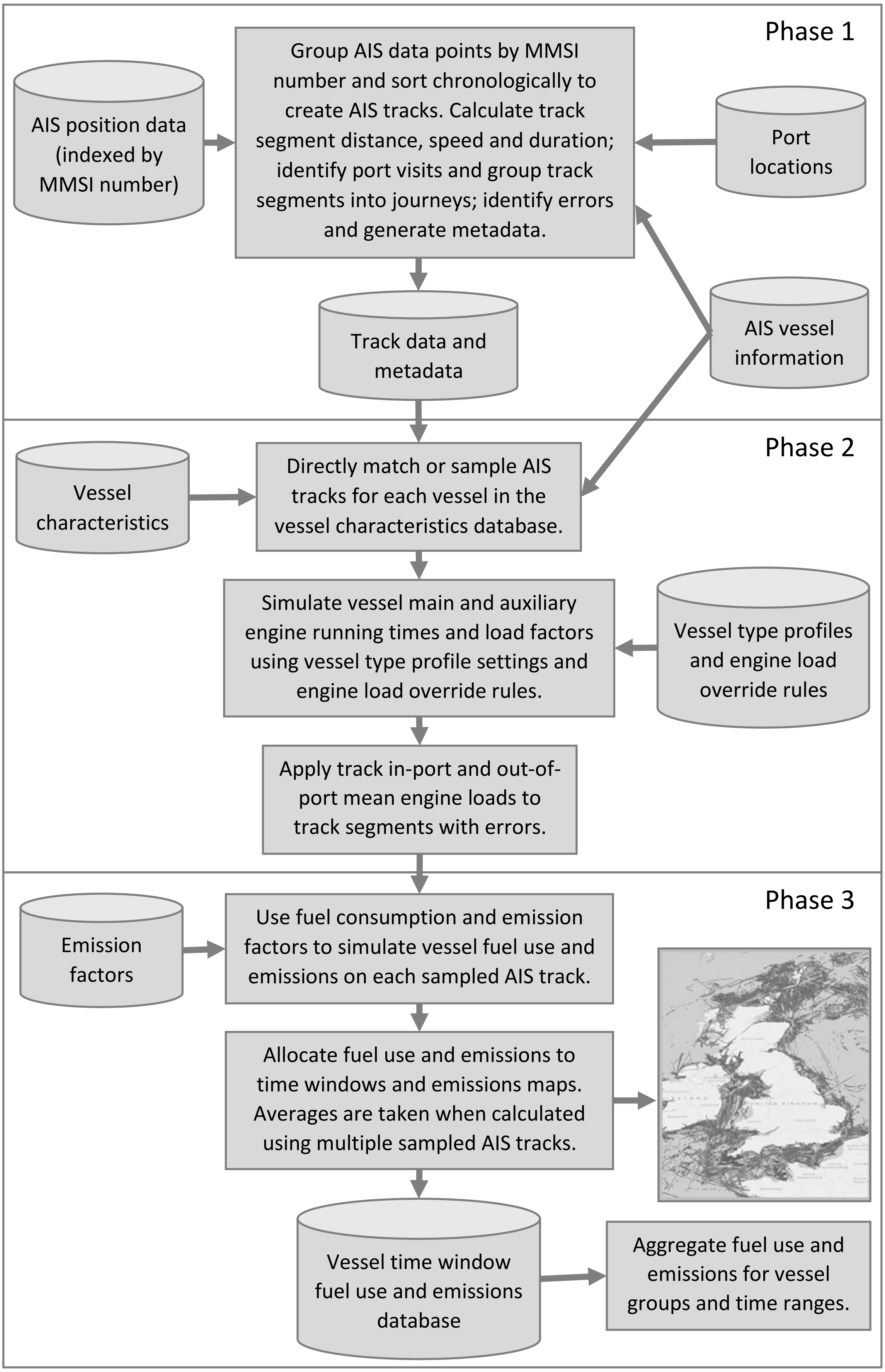

Figure 3.7. AIS data processing and emissions calculation methodology overview.

3.3.5 Phase 1: Processing AIS data to tracks

The raw AIS data are pre-processed. The nearest port to each AIS data point is identified by using the Haversine formula (Eq. 3.7) to calculate the great circle distance to each port in the port database (available in the CaseStudyData directory of the accompanying electronic material) and selecting the closest. Each AIS data point is also assigned to a geographic grid square, which represents an area on the globe, defined in decimal degrees to a user-specified resolution. For example, grid squares of 0.01° x 0.01° may be defined, thus dividing the globe into 6.48×10^8 grid squares.

For each unique MMSI number, all of the AIS data points identified with that MMSI number are grouped and sorted into chronological order to form a timeseries of vessel activity data referred to as an AIS track. Occasionally, multiple AIS data points within an AIS track share the same timestamp (see Figure 3.1, time interval of zero). This can occur because some AIS data providers represent AIS timestamps to the nearest minute and AIS devices can send multiple position messages per minute. One such AIS provider is *MarineTraffic.com* (MarineTraffic.com, 2013), the provider of the AIS data used during the development of this methodology. In this situation, an attempt must be made to sort the AIS data points into a sensible order. If not, the distance travelled by the vessel could be overestimated. Figure 3.8 illustrates this issue and the importance of sensibly ordering points sharing the same timestamp.

A reasonable assumption is that the vessel would have taken the shortest route connecting all of the data points sharing the same timestamp with the points immediately before and after them. Therefore, a routing algorithm that seeks the shortest path through the points is employed. There are N! possible routes that visit each point exactly once in a set of N points. The number of possible routes becomes extremely large as N increases. For example, with 5 points, there are 120 possible routes, with 8 points there are 40,320.

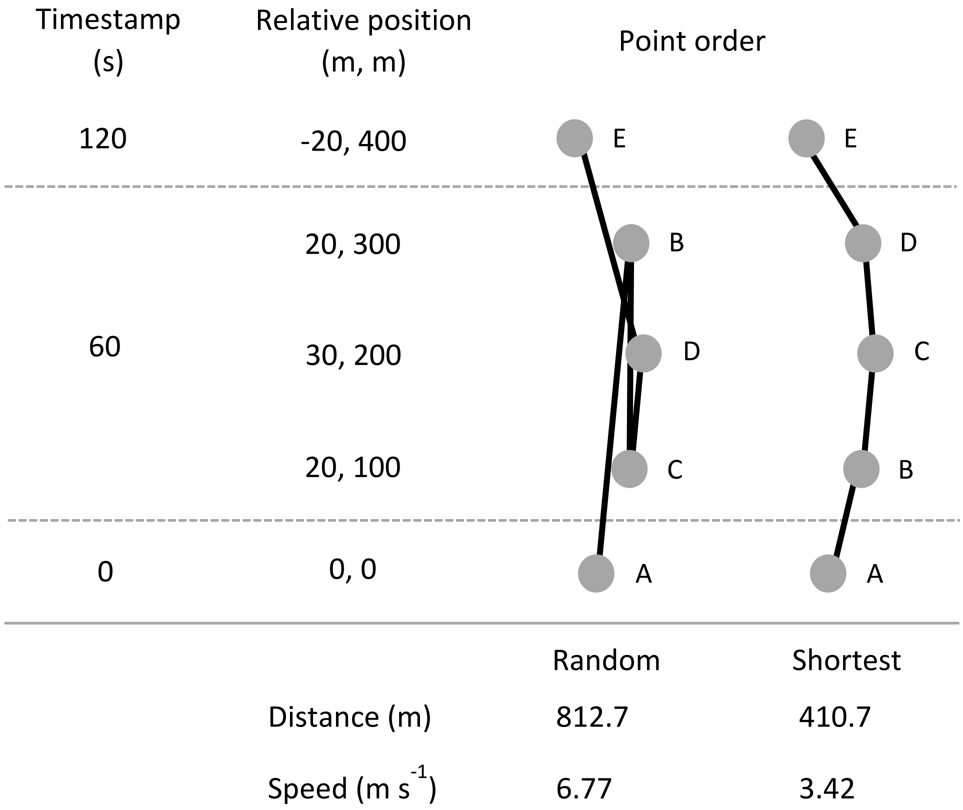

Figure 3.8. The importance of correct AIS data point ordering where multiple AIS data points in an AIS track share the same timestamp.

This is a form of a classic computer science problem referred to as the Traveling-Salesman Problem, for which no algorithm is knowns other than the brute-force approach of trying all possible routes that is guaranteed to find the shortest route (Cormen at al., 2011). It is known as one of the NP-complete problems in computer science. Since trying all possible routes becomes computationally intractable as N grows to even a relatively small number of points, numerous heuristic algorithms exist that find solutions that are generally close to optimal and can be computed efficiently even for large numbers of points. Perhaps the simplest and most computationally efficient is the nearest neighbour algorithm (Lin & Kernighan, 1973). This algorithm takes a random starting point and generates a route by iteratively travelling to the nearest of the remaining unvisited points until all points have been visited. This approach has been found to generate good, albeit not necessarily optimal, routes very efficiently.

The algorithm implemented to sort AIS data points sharing the same timestamp on an AIS track was almost identical to the nearest neighbour algorithm with the exception of having a fixed start and end point in the adjacent timestamps (as shown in Figure 3.8). Given the uncertainty surrounding the actual route taken and the low proportion of AIS data points sharing the same timestamp within AIS tracks (see Figure 3.1, time interval of zero), this quick approach was selected over a more complex and computationally expensive algorithm such as the algorithm presented by Christofides and Eilon (1972) that may, in some cases, generate a shorter route.

Once the data are sorted, track segments joining consecutive pairs of AIS data points are created and the distance, duration and speed of each are calculated. The length, in metres, of each track segment is calculated using the Haversine Formula (Sinnott, 1984), reproduced in Equation 3.7. The Haversine Formula calculates a close approximation of the distance between two points, described by their latitude and longitude, on the Earth's surface using spherical geometry.

$$a = \sin^2\left(\frac{\Delta\varphi}{2}\right) + \cos\varphi_1 * \cos\varphi_2 * \sin^2\left(\frac{\Delta\lambda}{2}\right) \qquad \text{Eq. 3.7}$$

$$c = 2 * \operatorname{atan2}\left(\sqrt{a}, \sqrt{1-a}\right)$$

$$d = R * c$$

Where:

φ = latitude

λ = longitude

d = is the great circle distance in metres between points φ_1, λ_1 and φ_2, λ_2

R = Earth's radius in metres (mean radius = 6,371,000 m)

The speed of a track segment is calculated in two ways. The first uses the speed recorded in the AIS data. The average of the speeds of the two AIS data points describing the track segment is used. This is similar to the method used by Jalkanen et al. (2009; 2012), where a speed for each second of a track is calculated by interpolation between the speeds of the AIS data points. The second uses the great circle distance, calculated using the Haversine formula, and duration of the track segment to calculate speed. This method was used by Olesen et al. (2009). The way in which these different speed calculation methods are used is discussed later in this section. The speed calculation methods are also compared (see Section 3.3.9 for method and Section 3.4.1 for results).

Where the timestamps of the two AIS data points are different, the duration is calculated as the difference between the timestamps. Where AIS data points share the same timestamp, a minor adjustment to the timestamps is made to reflect the assumed time intervals between all AIS data points sharing the same timestamp.

The interval is calculated using $\mathrm{I} = \frac{\mathrm{D_{max}}}{\mathrm{n}}$, where I is the assumed time interval between the AIS data points, $\mathrm{D_{max}}$ is the maximum possible time difference between AIS data points sharing the same timestamp. For the data used during model development, $\mathrm{D_{max}}$ is a minute and n is the number of AIS data points that share the timestamp. The altered timestamps are used during track segment creation and emissions calculation.

The fact that timestamps are rounded to the nearest minute potentially creates errors in the duration of track segments and, therefore, also in the track segment speed calculated from distance and duration (Table 3.5). In the data used during model development, timestamps are rounded to the nearest minute. Therefore, the duration of any track segment has a maximum uncertainty of ±1 minute (±30 seconds for the AIS points at either end).

The impact of the uncertainty decreases as the duration of track segments increases. Therefore, one way of decreasing uncertainty is to collect track segments into groups with a duration that limits uncertainty to an acceptable level and calculate an average speed for the group. The minimum duration of track segment groups is user-definable in the software produced and a default value of 20 minutes was used. Track segments are added to a track segment group until the minimum duration has been reached and a speed is calculated from the aggregate distances and durations (e.g. Figure 3.9).

Table 3.5. Effect of timestamp uncertainty on calculated track segment speed, assuming a track segment distance of 1 nautical mile.

Recorded duration (mins)	Min possible duration (mins)	Max possible duration (mins)	Speed (knots)	Minimum possible speed (knots)	Maximum possible speed (knots)
2	1	3	30.00	20.00 (-33.3%)	60.00 (+100.0%)
5	4	6	12.00	10.00 (-16.7%)	15.00 (+25.0%)
10	9	11	6.00	5.45 (-9.1%)	6.67 (+11.1%)
15	14	16	4.00	3.75(-6.3%)	4.29 (+7.1%)
20	19	21	3.00	2.86 (-4.8%)	3.16 (+5.3%)
25	24	26	2.40	2.31 (-3.8%)	2.50 (+4.2%)
30	29	31	2.00	1.94 (-3.2%)	2.07 (+3.4%)
60	59	61	1.00	0.98 (-1.6%)	1.02 (+1.7%)

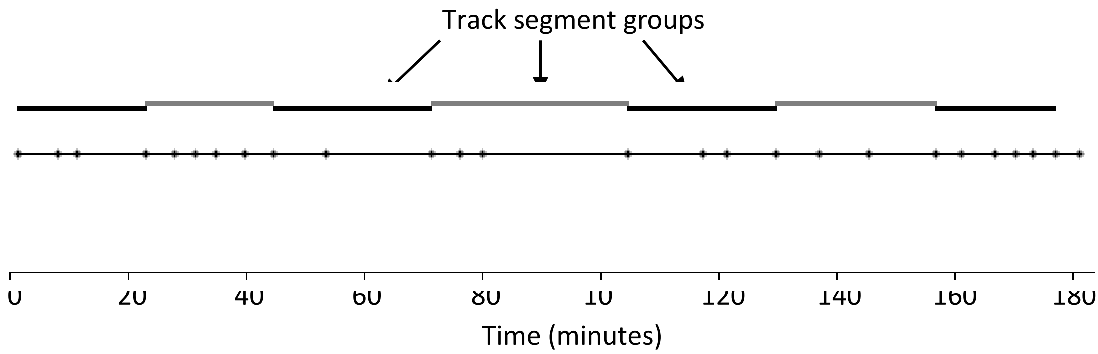

Figure 3.9. Creating track segment groups of a minimum specified length from AIS data. Example of a track segment group with minimum duration of 20 minutes.

In addition to calculating track segment distance, duration and speed, track segments are also categorised based on their proximity to ports within the ports database and whether the track segment is deemed to be moving or not. The maximum distance from a port's coordinates to consider as a port area is user-definable, and all track segments are classified based on whether the start and end points are within a port area. The minimum speed to be considered moving is also configurable. This is used to classify track segments as either moving or stopped (Table 3.6).

When using speed calculated from distance and duration, it is recommended that the minimum moving speed is chosen with care to avoid incorrectly calculating fuel use and emissions for minor movements generated by GPS noised and drifting of vessels whilst moored or at anchor. When using speed calculated from the speeds in the AIS data, zero can be taken as not moving as AIS speeds have a resolution of 0.1 knots and so vessels in port and at anchor would not be expected to register speeds other than zero.

Table 3.6. Track segment classification based on proximity to ports and whether the vessel was moving for the track segment.

Start AIS data point	End AIS data point	Moving?	Track segment classification
In port	In same port	No	Stopped in port
In port	In same port	Yes	Moving in port
In port	In different port	-	Moving between ports
In port	Not in port	-	Leaving port
Not in port	In port	-	Entering port
Not in port	Not in port	No	Stopped not in port
Not in port	Not in port	Yes	Moving not in port

Chronologically consecutive track segments that are classified as being stopped are grouped into ‘stops’, for which an average location is calculated. The duration of the stop is also calculated, which is significant when applying assumptions about main and auxiliary engine activity during stops (Section 3.3.6). If a stop is within a port area, the port ID is assigned to the stop, allowing stops to be associated with countries.

After all track segments have been created, tracks are analysed for applicable *engine load override rules* and maximum speeds for each track are calculated. The maximum speed is calculated so that it can be used as a proxy for design speed during engine load calculation, in the absence of vessel design speed data for the vessels that created each of the AIS tracks.

It was found that the absolute maximum speed of a track was often unrealistically high (e.g. > 100 km h^{-1}). The reasons for this were unknown, but it was considered to be erroneous data, probably caused by technical malfunctions. Calculating a maximum speed that is registered for a minimum cumulative duration, e.g. 20 minuts, was considered a reasonable way to address this issue. This approach allows the empirical data to be used to identify maximum speeds, but also avoids setting the maximum speeds to unrealistically high values registered only very briefly.

In order to do this, track segments were bucketed into speed groups with a specified resolution (e.g. 0.1 km h^{-1}) and the total duration of track segment in each group was calculated. Using these groups, the maximum speed that is registered for a specified minimum cumulative duration can be calculated by sorting the speed groups into descending speed order and then iteratively accumulating the durations. Once the cumulative duration reaches the specified minimum value, the most recently added speed group is taken as the maximum speed that is registered for the minimum cumulative duration. The vessel design speed, taken either from the vessel database, or derived from the AIS data, and the track segment instantaneous speed is used to calculate a relative speed for each track segment ($\frac{V_i}{V_d}$).

Finally, the activities of vessels between visits to ports in the port database are processed as journeys with origin and destination ports. This could be used to allocate emissions between the countries of departure and arrival. However, emissions allocation was outside of the scope of this project given that the case study data were for a domestic fishing fleet.

3.3.6 Phase 2: Calculating engine load

Emissions are calculated for each vessel in the vessel characteristics database. This is done by matching each vessel to one or a sample of AIS data tracks depending on whether the vessel can be directly matched to a single AIS data track using an MMSI number. For a brief overview of sampling methods used when one-to-one matching of a vessel to AIS activity data is not possible, see Section 3.3.2. For an in-depth treatment of sampling, see Chapter 4.

One of the key variables in emissions calculation is the relative speed ($\frac{V_i}{V_d}$) of a vessel at any given time. This is used to calculate engine load factors (LF). Because two different methods are used to calculate speed, each track segment has a range of possible values for speed and, in turn, relative speed. For this reason, there are different modes that can be used during emissions calculation. There is a mode using each of the speed calculation methods, and there is a third combined method that makes use of both. The different speed calculation methods are compared later in this chapter. The methodology for comparison is described in Section 3.3.8 and results are presented in Section 3.4.1. Various different speed calculation methods are also trialled in Chapter 5 to determine the sensitivity of model results to the speed calculation method used (see Section 5.4.1 for results).

Vessels cannot travel less than the shortest possible distance between two consecutive AIS data points, although they may travel further. The shortest distance between two points on the surface of a globe is called the great circle distance. This is the distance that is calculated by using the Haversine formula (Eq. 3.7). Given that the duration of each track segment is known, the speed calculated from the great circle distance should be considered a minimum possible speed for the vessel between any two consecutive AIS data points.

The speeds recorded in AIS data are only an instantaneous 'snap-shot' of a vessel's speed. Therefore, the actual average speed travelled between two AIS data points is quite likely to differ from the average of the two AIS data point speeds, especially for track segments with a relatively long duration. Nevertheless, if the mean of the speeds recorded in two consecutive AIS data points is higher than the speed calculated from the great circle distance, this may suggest that the vessel travelled a longer route between the AIS data points and was moving at a higher speed.

To utilise the information that both speed methods provide, a new combined method has been introduced as part of this project where the higher of the two speeds associated with each track segment is chosen and engine load is calculated from the associated speed relative to maximum. A comparison of these different speed calculation approaches is shown in Section 3.4.1.

The AIS data track or sample of tracks provide the track segment duration (T) and the engine load factor (LF) used in emissions calculation (Eq. 3.4). Some of the data quality issues identified and discussed in Section 3.2.3 can lead to significant errors in the speed calculated for track segments, which also has a significant impact on the LF calculated. Therefore, it is necessary to identify and attempt to correct any errors in the data to avoid potentially significant errors in the emissions inventory produced.

The two types of error that this methodology addresses directly are errors to do with track segments that have an unusually long duration (indicative of network coverage issues, as depicted in Figure 3.5) or an unrealistically high speed. Track segments with an unusually long duration can be caused by vessels operating outside of receiver network range, equipment malfunction and receiver station overload. Track segments with an unrealistically high speed could be caused by equipment malfunction. These errors are identified by analysing each track segment and comparing the duration and speed to maximum values set in the model's configuration files. Track segments are then flagged as containing duration errors, speed errors, or both.

The engine loads of all track segments without errors are calculated. For all track segments for which the vessel is moving, the load factor of the main engine is calculated from vessel speed, as described in Section 3.3.3. When stopped, however, assumptions must be used to estimate the load factor of the main engine. For each *vessel type profile*, an engine load factor is specified for when the vessel is hotelling with the main engine running. The proportion of a stop that the main engine is assumed to be running is also specified. Minimum and maximum main engine running times can also be set to more realistically model particularly brief or prolonged stops where using a proportion of the time would be unrealistic. For example, if the AIS data showed a vessel to have stopped for 2 minutes, it is realistic to assume that the main engine was running throughout the duration of the stop.

For longer stops, where it is reasonable to assume that the main engine was turned off during the stop, the time that the engine is modelled as running is split equally between the start and end of the stop. A stop is often made up of multiple track segments. For each track segment within a stop, the proportion of its duration that the main engine is assumed to be running is calculated based on the cumulative time since the start and before the end of the stop. Where the main engine is modelled as running for a proportion of the duration of a track segment, the engine hotelling load factor specified in the *vessel type profile* is multiplied by this proportion to give an appropriate average engine load for each track segment. The same method is used for calculating auxiliary engine loads and running times while stopped, with specific load factors and running time settings for the auxiliary engine also being specified in the *vessel type profile*.

AIS data provides relatively little information that can be used to determine auxiliary engine loads while a vessel is moving. There are, however, recommendations set out in the *EMEP/EEA air pollutant emission inventory guidebook 2016* (Trozzi et al., 2016) for different engine load factors to apply for auxiliary engines during cruising, manoeuvring and hotelling operations. These are 30%, 50% and 40% respectively (except tankers, where a hotelling load factor of 60% is suggested). To reflect this, engine load factors can be specified for auxiliary engines during manoeuvring and cruising, as well as hotelling, in each *vessel type profile*.

In order to apply these engine loads, a moving vessel must be classified as either manoeuvring or cruising. This is done on the basis of the load factor calculated for the main engine for each track segment. A maximum manoeuvring load factor is specified for the main engine in each *vessel type profile*. When the vessel is moving with a main engine load below this limit, the vessel is considered to be manoeuvring. Otherwise, the vessel is considered to be cruising. On the basis of this classification, an auxiliary engine load is applied to each track segment.

In the *EMEP/EEA air pollutant emission inventory guidebook 2016* (Trozzi et al., 2016) it is suggested that 20% is a typical main engine load factor for vessels while manoeuvring. Given that this is a typical manoeuvring engine load, a slightly higher value should be taken as the maximum. Based on this, a maximum manoeuvring main engine load factor of 30% was selected for the case study fleet and applied to all *vessel type profiles*. The sole purpose of this limit is for the classification of movement as either manoeuvring or cruising so that an appropriate auxiliary engine load factor can be selected.

After this initial pass of engine load calculation is completed, each track segment without errors has an engine load for both the main and auxiliary engines. However, a second pass is required to handle errors and apply any *engine load override rules* associated with the vessel's *vessel type profile*.

To apply *engine load override rules*, groups of track segments that meet the conditions for any *engine load override rules* associated with the vessel are identified. *Engine load override rules* have both a speed and duration range. Therefore, if a track segment or series of consecutive track segments is identified that is within the speed range, the duration that the vessel was travelling within the speed range is calculated. IIf the duration criteria for the particular *engine load override rule* are met, the engine load factor of the track segment or group of track segments is set to the value specified in the *engine load override rule*.

For track segments with errors, an average engine load is applied that is calculated from the track segments in the same track that do not have errors. Track segments are grouped based on whether the vessel is in port or not. According to the categories in Table 3.6, track segments that are 'stopped in port' and 'moving in port' are considered 'in port' track segments. All other track segments are considered to be 'not in port'. Average engine loads are calculated for both of these groups of track segments using only the track segments that do not have errors. These averages are then applied to the track segments of the same type that have errors.

3.3.7 Phase 3: Emissions calculation

Once engine loads have been calculated, the AIS track or tracks being used to calculate emissions for a given vessel are split into a series of time windows for emissions calculation. Using time windows makes it simpler to average emissions, because the emissions produced by simulating the vessel travelling along multiple AIS tracks within a single time window can be summed. The duration of these time windows is user-definable. In this project a time window duration of 1 hour was used. Where a track segment spans multiple time window, it is split between the time windows proportionally, based on the duration of the track segment within each time window.

Emissions are then calculated for both main and auxiliary engines using the duration of each track segment or partial track segment within each time window (T); the engine load factor (LF) for the specific engine; the nominal power (P) of the specific engine from the vessel characteristics database; and any sets of emission factors (EF) associated with the engine multiplied by their probability (C) (Eq. 3.4). When there is uncertainty over the specific engine used, multiple engines can be associated with each vessel, along with their probability. The set of probabilities associated with engines must always sum to 1.0. Where the specific type of engine used by the vessel is known, this engine is given a probability (C) of 1.0.

Specific fuel oil consumption rates and emission factors are selected from a database of emissions factors based on the *EMEP/EEA air pollutant emission inventory guidebook 2016* (Trozzi et al., 2016). Specific emission factors are applied based on the engine and fuel type of main and auxiliary engines, vessel age and the operating mode of the track segment for which emissions are being calculated. When a sample of AIS tracks is used, the average emissions within each time window are calculated and used as the emissions for the vessel during that time window.

If any emissions maps have been defined, the emissions calculated for each track segment or partial track segment are also allocated proportionally to any grid squares intersected by the track segment. This results in a map of the total quantity of each pollutant emitted in each grid square. It should be noted that emissions maps will have inaccuracies when using sampling to associate vessels with AIS data as emissions will only be allocated to grid squares intersected by the tracks in the AIS data. Given that all vessels are modelled as travelling along these tracks, the emissions maps produced will overestimate emissions in the grid squares intersected by these tracks and may underestimate emissions elsewhere. However, the maps produced can still serve as an indication of the overall pattern of vessel activities and their atmospheric emissions.

3.3.8 An example vessel

In this section, a simple fictional example will be given to help elucidate the fuel consumption and emissions calculation process described in the previous sections. A single vessel will be the subject of this example. Since the emissions calculation methodology was developed for a case study fleet of UK fishing vessels, the fictional subject of this example will be a fishing trawler. Let's imagine that we want to calculate fuel consumption and emissions for this vessel for one year.

Some vessel characteristic data are available for this trawler, such as main and auxiliary engine power and it's age. The vessel has a main engine power of 350 kW. We also know that it belongs to the UK fishing fleet. However, the vessel's design speed, an important piece of information required for fuel consumption and emissions calculation is not known. For the sake of simplifying the example, let us imagine that the vessel has a Class-B AIS device installed and that the vessel's MMSI number is known.

In this example, the operator of a terrestrial AIS receiver network has offered to provide AIS data for the calculation of fuel consumption and emissions for the vessel. Since the vessel's MMSI number is known, the AIS position messages indexed by that specific MMSI number can be identified and retrieved by the AIS data provider for the year in question.

These AIS data points (in excess of 30,000 individual messages), when sorted chronologically, produce an AIS track that describes the trawler's activities for the year in question. Imagine this AIS track is processed as described in Phase 1 (Section 3.3.5), creating track segments between each consecutive pair of AIS data points. Each of these track segments has a distance, duration and speed. However, because the vessel's design speed is unknown, a proxy is required in order that the relative speed of each track segment can be calculated. It is the relative speed that is required in order to calculate engine load (Section 3.3.3), which in turn is used to calculate emissions (Eq. 3.3).

It seems reasonable to assume that the vessel will travel at its design speed for at least some time during the year. It also seems reasonable to assume that it will rarely, if ever, exceed its design speed. Therefore, the maximum speed that the vessel travels over the course of the year is considered a reasonable proxy for design speed. The AIS track is scanned to find the maximum speed. However, the result is a speed of 102.1 knots, which doesn't seem realistic. This is probably indicative of an error in the data. Therefore, the maximum speed that the vessel travelled at (or above) for at least 20 minutes is taken instead. This yields a more reasonable value of 12.0 knots. This is used as a proxy for design speed to calculate the relative speed for each track segment.

From the speeds of the track segments we can also determine when and where the vessel stopped (speeds approaching 0.0 knots). From the location of these stops, it is also possible to determine when the vessel stopped in the proximity of ports. On this basis, the AIS track spanning the entire year can be split into a series of journeys, punctuated by port visits. The remained of this example will consider just one of these journeys.

The vessel has been stopped for several days. From its location, it appears to have been stopped in a port. Then, the vessel begins to move and this movement is registered by the AIS device onboard and broadcast in AIS messages. We deduce that the vessel's main and auxiliary engines must have been running for some time before the vessel started moving. This is calculated as described in Section 3.3.6 and the track segments that make up the stop are adjusted to reflect this assumption with appropriate main and auxiliary engine loads. The AIS data shows the vessel moving slowly (<50% of its design speed of 12.0 knots) for a few minutes. The main engine load is calculated as between 20 and 30%. This is classified as the vessel manoeuvring out of port as it begins its journey and an appropriate auxiliary engine load is assigned.

The AIS data then shows the vessel picking up speed to travel at 70-100% of its design speed for approximately two hours. This is classified as cruising, allowing an auxiliary engine load to be selected and applied. The vessel then slows and stops for 10 minutes before setting off again at between 2.8 and 3.0 knots, continuing for approximately 3 hours, and then stops for 30 minutes. This 3 hours of slow movement is identified as trawling based on the *engine load override rule* criteria for the vessel (see Table 3.4), and an engine load of

75% is applied. The stops either side of the trawling are also short enough that the main engines are modelled as running for the duration of each stop.

The AIS data then shows the vessel starting to move again at approaching its design speed for a few minutes before a gap in the AIS data of 5 hours. The speed calculated using great circle distance for the 5 hour track segment between consecutive AIS data points is just 0.8 knots, but the speed at either end is around 10 knots. The duration of this track segment indicates that the vessel travelled outside of AIS network range, so the track segment is classified as containing errors. Once back in range, the AIS data then shows the vessel returning to the same port that it left several hours before, slowly manoeuvring into port and then stopping. Again, the main and auxiliary engines are modelled as running for some time after the vessel has stopped and appropriate engine loads are applied.

A series of similar journeys are observed throughout the year. Engine loads are calculated for main and auxiliary engines for all of the track segments on these journeys and the stops that separate them, with the exception of track segments with errors, like the 5 hour track segment observed in the journey described above. In order to apply a reasonable engine load to these track segments with errors, the mean main and auxiliary engine loads are calculated for all track segments when the vessel was in port as well as all track segments when the vessel was not in port. These mean engine loads are then applied to track segments where errors have been identified on the basis of whether the error track segments happen within or outside of the proximity of ports.

The track segments, now all with main and auxiliary engine loads assigned, are used along with the technical information known about the vessel as inputs to the emissions calculation formula (Eq. 3.3). The main and auxiliary engines of the vessel are both High-speed Diesel (HSD) engines that run on Marine Diesel Oil (MDO). Along with the vessel's age, this information is used to select appropriate emission factors for all types of activity (cruising, manoeuvring and hotelling) for both main and auxiliary engines. These emission factors are assigned a probability of 1.0, given that there is no uncertainty about the engine and fuel types in use. The emissions associated with each track segment are calculated using the appropriate set of emission factors depending on whether the vessel was cruising, manoeuvring or hotelling during that track segment.

The track segments are then aggregated and, when necessary, split into time windows of an hour in length. These emissions are stored for the vessel and can later be analysed further such as by aggregating them with other vessels' emissions within specific time periods.

3.3.9 Comparison of speed calculation methods

As described in Section 3.3.4, two speed calculation approaches were used to produce two separate values of speed and relative speed for each track segment. The concept of a combined speed value was also introduced, which is the higher of these two speeds (see Section 3.3.5). The speed method used affects both the instantaneous speed assigned to each track segment and the derived design speed values (see Section 3.3.4). Both of these are important inputs to the engine load calculation formula. Therefore, the speed calculation method used will have a significant effect on results.

By way of a simple comparison of the different methods, summary statistics were calculated for the entire AIS dataset containing the speeds and relative speeds (speed as a ratio of design speed) of all track segments. The same metrics were also calculated for just track segments classified as moving. The average percentage of track segments classified as moving and the average maximum speeds registered on tracks were also calculated. These statistics were calculated for the three different speed methodologies introduced in Section 3.3.4. Tracks with fewer than 1000 AIS data points were excluded on the grounds that they were considered to be unrepresentative of a vessel's annual activity. Only track segments without errors were included in the averages calculated. The results of this analysis are presented in Section 3.4.

3.4 Speed calculation method comparison and error handling results

3.4.1 Speed calculation method comparison results

Of the AIS tracks grouped by the 5,188 unique MMSI numbers in the AIS dataset, 3,960 had at least 1,000 AIS data points. The metrics calculated show that the AIS-based speed method records more movement than the Haversine distance-based speed calculation method (Table 3.7). However, the Haversine speed method produced higher average speeds whilst moving as well as considerably higher maximum speeds. The combination of lower maximum speed, used as a proxy for design speed, and a higher proportion of time spent moving meant the AIS speed method generated a higher mean relative speed. The combined method, where the higher of the Haversine and AIS speeds is used, produces a higher mean speed. However, due to higher maximum speed, the mean relative speed that it produces is between those of the Haversine and AIS methods.

Table 3.7. Summary activity statistics for the different Haversine, AIS and combined speed calculation methods applied to all tracks with at least 1000 AIS data points.

	AIS	**Haversine (distance / time)**	**Combined**
Moving (%)	43%	36%	44%
Mean speed (knots)	1.71	1.62	1.81
Mean speed whilst moving (knots)	3.95	4.49	4.13
Mean track max speed (knots)	13.62	18.48	20.18
Mean relative speed (knots/knots)	0.132	0.085	0.091
Mean moving relative speed (knots /knots)	0.305	0.234	0.208

3.4.2 Error handling

To give an indication of how error handling works, it is convenient to refer to emissions maps produced by the emissions modelling software. Maps that include track segments found to be in a state of error give a good indication of where erroneous data are being used in emissions calculation. Figure 3.10 shows a significant number of track segments that appear to cross land masses. However, the same map containing only track segments found not to have errors displays no track segments crossing land masses (Figure 3.11).

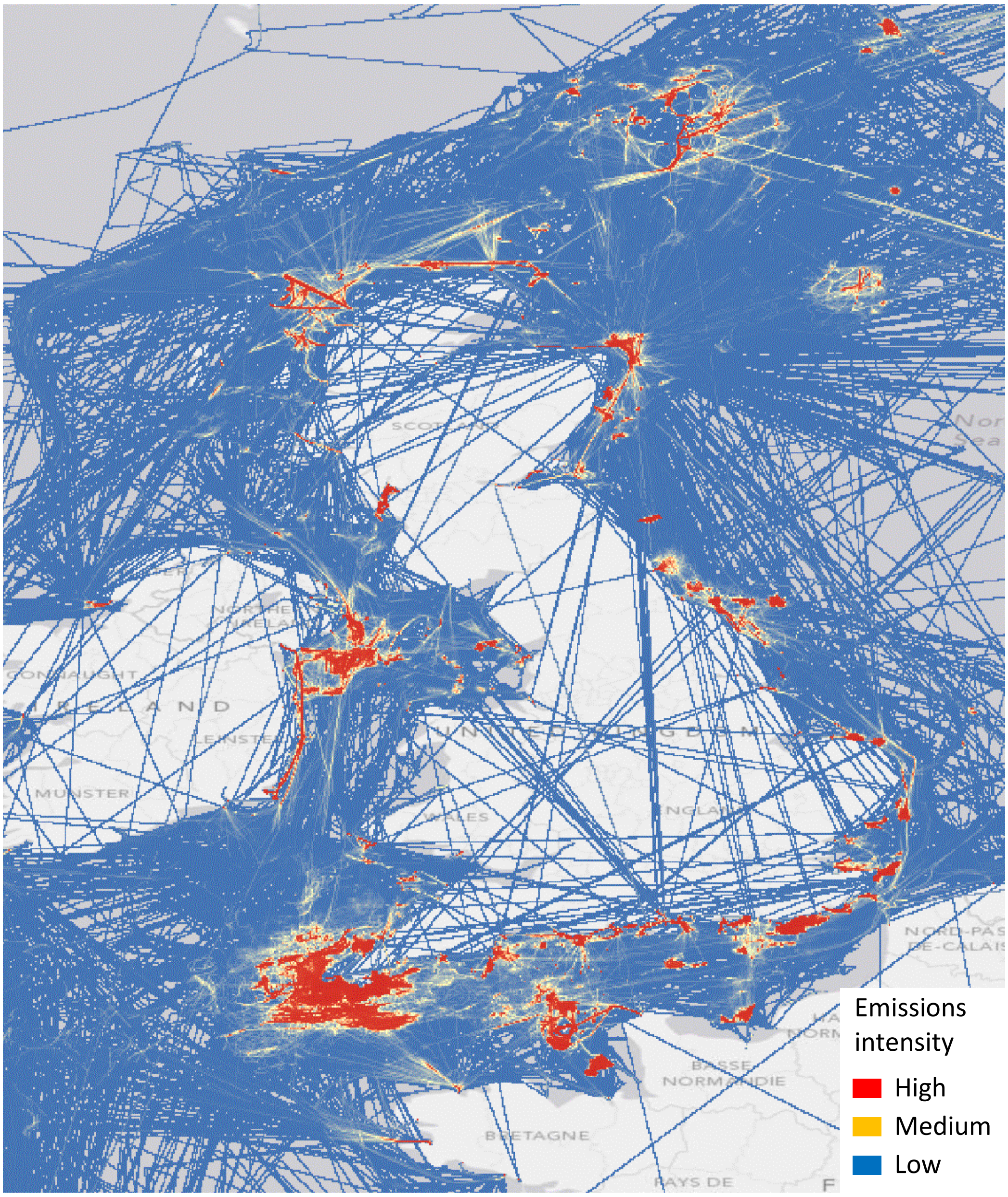

Figure 3.10. CO_2 emissions from the UK fishing fleet May 2012-May 2013 mapped in 0.2° x 0.2° grid-squares including track segments defined as having errors.

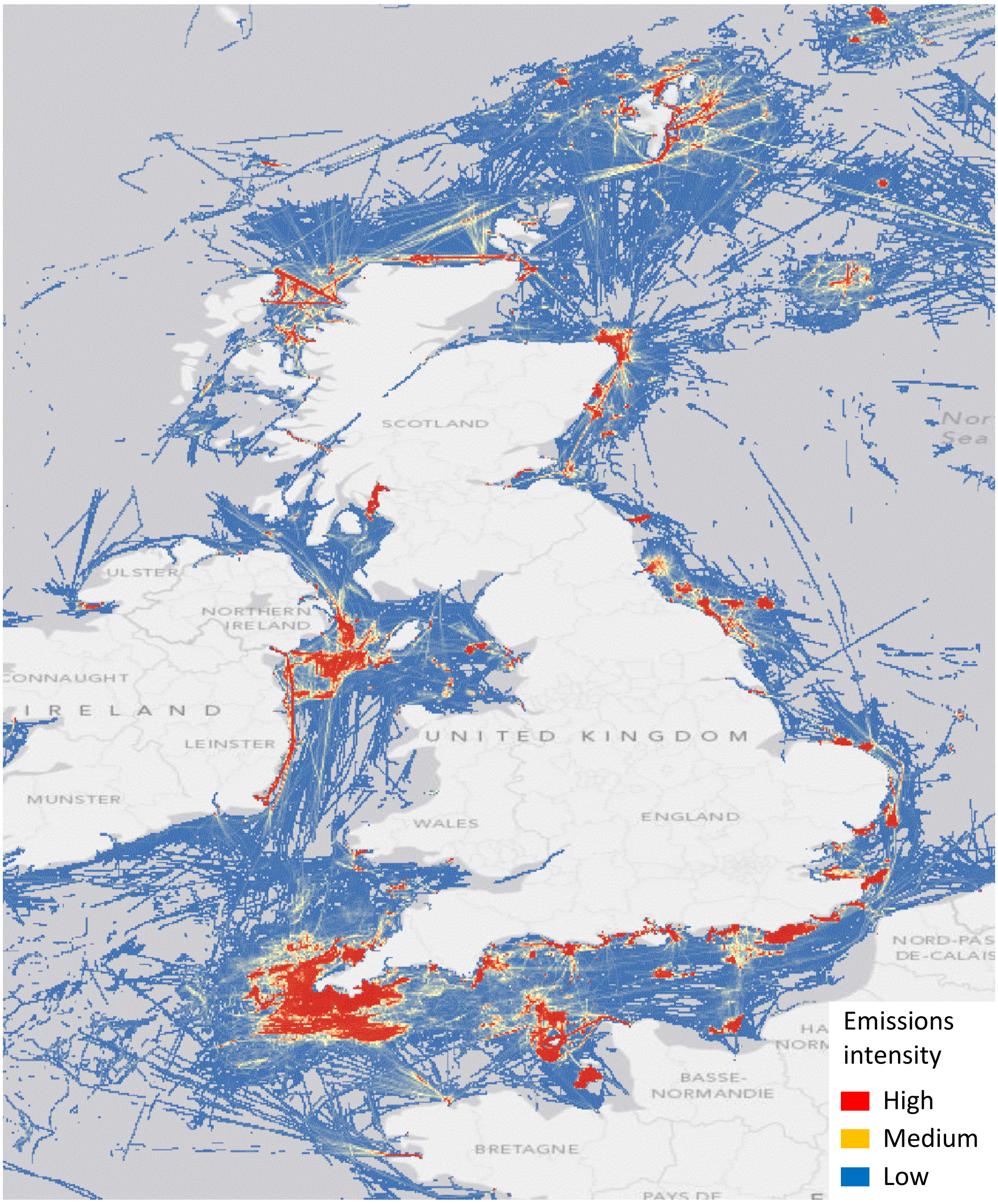

Figure 3.11. CO_2 emissions from the UK fishing fleet May 2012-May 2013 mapped in 0.2° x 0.2° grid-squares excluding emissions between AIS points with a time interval of greater than one hour or an average speed in excess of 100 km h^{-1}.

3.5 Discussion

The methods and software introduced in this chapter offer a new activity sampling approach designed to overcome the challenge of using AIS data to model emissions of vessels that cannot be directly matched to AIS activity data either due to a lack of information required for matching or because AIS data for a particular vessel are unavailable. This approach is predominantly meant to facilitate the use of AIS data for modelling emissions from small commercial watercraft. The focus on error handling offers advantages over previous approaches that do not tackle errors so well (Jalkanen et al., 2009; 2012; Olesen at el., 2009; MARIN, 2012). Similar error handling methods have subsequently been used in *The IMO Third GHG Study* (Smith et al., 2014).

One of the key ways that errors are detected is through the identification of track segments with a duration exceeding a defined maximum value. Setting a maximum value is somewhat subjective. However, creation and inspection of AIS track statistics, e.g. Figures 3.3 and 3.4, can help in selecting a reasonable value. From the analysis performed on the data used in this study, a value of 30 or 60 minutes seems reasonable. However, this may differ for other types of vessel and AIS datasets.

An example of this is shown in Figures 3.10 and 3.11, where track segments with duration above 60 minutes have been classified as erroneous. It is clear from Figure 3.10 that using the shortest distance travelled without error detection and handling leads to the creation of track segments that apparently travel over land, which is clearly wrong. Calculating speed and engine load for these tracks would be expected to result in erroneous results either due to an underestimation of distance travelled or because the time interval is too great for AIS speeds to be taken as a reasonable indication of the entire track segment's speed. Figure 3.11 shows the same map but with track segments over 60 minutes in duration treated as errors and removed from mapping. These segments would be assigned an average engine load calculated from the rest of the track. This gives a much more realistic map, which suggests that the use of these track segments to calculate speed and engine load is likely to give better quality results.

The approach also offers a means to compare the effect of using different speed calculation methods. This is a subject deserving investigation given that previous studies, e.g. Jalkanen et al. (2009; 2012) and Olesen at el. (2009) have used different speed calculation methods without justifying the use of one over another.

Comparison of the two speed calculation methods shows that, there are significant differences between the speeds contained in the AIS data and the speeds calculated using the distance and time interval between consecutive AIS data points. Speeds calculated from the values contained in the AIS data tend to be lower than those calculated using track segment distance and duration. If using a common value for design speed with both speed calculation approaches, emissions results calculated from AIS speeds (e.g. Jalkanen et al., 2009, 2012) are likely to be slightly lower than results calculated from speeds deduced from track segment distance and duration (e.g. Olesen et al., 2009).

However, if using a maximum speed calculated from the data as a proxy for design speed, the results for relative speed tell a different story. This is because relative speed is calculated by dividing track segment speed by design speed. Design speeds were not known for the case study fleet so the maximum speed maintained for a minimum cumulative duration of 20 minutes is used as a proxy for design speed. In this case, the AIS speed calculation method produces a lower maximum speeds and, therefore, significantly higher relative speeds than either of the other methods.

Overall, the relative sizes of the emissions results calculated are likely to be similar to the mean relative speeds calculated for the three speed calculation methods. Based on this assumption, the Haversine speed method is likely to produce the lowest fuel use and emissions estimate, the hybrid method slightly higher and the AIS speed method is likely to produce the largest values for results.

One area where this methodology could be improved is in the sophistication of the main engine load calculation procedure. For example, Jalkanen et al. (2009; 2012) use a methodology that explicitly factors in added resistance in waves. This would be expected to yield better results than a methodology that does not, such as this, and the majority of other activity-based methods. However, Jalkanen et al. (2009; 2012) do not handle the data quality issues highlighted in this methodology. Inclusion of added resistance in waves could be modelled in the software developed with minor adaptations using a methodology similar to that developed by Dedes (2013). Using such a methodology has been shown to reduce uncertainty in emissions calculation significantly.

The method used for AIS track sampling was briefly touched upon in Section 3.3.2. The selection of an appropriate AIS track sampling approach is one of the aspects of this methodology that is significantly different from AIS-based emissions calculation methods published in the literature. For this reason, the influence of changing the criteria used for AIS track sampling is given an in-depth treatment in Chapter 4.

Discussion of the various factors causing uncertainty within the fuel use and emissions calculated using this methodology has also been minimal within this chapter. This is a complex subject, which is addressed in detail within Chapter 5.

Finally, a case study of using this method to calculate emissions from the UK fishing fleet over a year is presented in Chapter 6. The advantage of using the UK fishing fleet as a case study was that an alternative proxy-activity-based method to emissions calculation could be used alongside this AIS-based method. By using multiple methods, this goes some way to validating the result produced using the AIS-based methodology presented in this chapter.

3.6 Conclusions

The use of AIS data for the production of emissions inventories for shipping data offers significant advantages over other sources of activity data. The emissions inventories generated are more reliable and detailed and the data naturally lends itself to the production of high-quality temporally and geographically resolved emissions inventories.

However, when using AIS data there are several data quality issues that should be considered to avoid potentially significant errors in the emissions inventories produced. Handling these errors is important if AIS data are to be used for the calculation of emissions inventories. The methods proposed in this chapter offer a solution to the most important of these data quality issues. Namely, the existence of prolonged gaps in the AIS data record and the occurrence of unrealistically high speeds.

The speed calculation methodology to use must be chosen carefully. Analysis of the data made available for model development has shown that there are significant differences in the results of the three speed calculation methodologies examined in this chapter. Given the importance of a vessel's speed during emissions calculation, this subject should be afforded considerable attention by researchers in order that the most robust methodology can be identified.

Based on the thought and investigation undertaken in the development of this methodology, it is considered likely that the use of a hybrid speed calculation methodology yield more accurate results. Calculating speeds from distance and time provides a useful minimum speed, while higher AIS speeds can serve as an indicator of when vessels not travelling the shortest possible path between AIS data points.

The methodology presented in this chapter offers a flexible and robust approach for producing high quality spatially and temporally resolved shipping emissions inventories for all types of vessel for which a reasonably large proportion of the fleet broadcasts AIS messages. Importantly, the use of activity sampling where one-to-one matches between vessel data and AIS data records cannot be achieved makes this methodology applicable to fleets of small commercial watercraft where some vessels do not use AIS technology or where the data necessary to match vessels to AIS records is unavailable. Methods such as this are the state-of-the-art in shipping emissions inventory calculation and will be easily and quickly applicable as access to AIS data improves and mature software tools for the processing of AIS data are established.

4 Selecting appropriate activity sampling criteria

The purpose of this chapter is to explore the different filtering criteria that can be used when sampling AIS tracks for the calculation of fuel use and atmospheric emissions from vessels that cannot be directly matched to specific AIS data. The effects of varying the different filtering criteria are investigated and a set of sampling criteria are suggested for the case study fleet and AIS data used in this project. This chapter helps to satisfy objective 2 of this project:

> *"To create a robust, repeatable and practical methodology for the calculation of atmospheric pollution caused by small commercial watercraft"*

4.1 Introduction

Vessel activity is the most significant factor in the generation of atmospheric pollution emissions. Emissions are a function of activity, namely engine operating time and engine load, vessel engine type and power, and emission factors (see Eq. 3.4 and 3.6). Emission factors are also partially reliant on activity given that their selection is based on a combination of activity mode and vessel characteristics.

When using a sampling approach to associate vessel data with activity, it is of great importance to ensure that the sampling approach used gives a fair representation of the likely activity of the vessels being modelled. It is, or course, impossible to gain certainty that the sampled activity data are a good representation of each individual vessel. This would only be possible by directly matching vessels to their individually generated AIS tracks. However, where one-to-one matching of vessel data to AIS tracks is not possible, care must be taken to ensure that an appropriate sample of activity tracks is selected. This includes both the size of sample (number of tracks selected per vessel) and the method by which that selection is made. The aim is to arrive at a sampling approach that makes good use of the available activity data, where no tracks are selected so frequently as to significantly skew the results.

The sampling approach devised for this study uses the proportion of track segments with errors, overall track duration, AIS data point counts and proportion of stops at countries to filter tracks for sampling for vessels. For example, an approach for the UK fishing fleet could be to select tracks with errors in no more than 10% track segments, at least 50% of port calls at UK port, a minimum of 1,000 AIS data points and a total duration (time between first and last AIS messages in the track) of at least half a year.

In addition to these filtering criteria, some basic data, including length, were obtainable on the vessels associated with the AIS tracks by automatically extracting information from publicly available data accessible through the MarineTraffic website (MarineTraffic.com, 2013). Length was trialled as a basis for stratified sampling within the wider group of viable AIS tracks. This was attempted on the basis of an assumption that vessels of a similar size are more likely to have a similar activity profile than vessels of considerably different sizes. The length is used to initially narrow the group of tracks from which a sample is drawn to only tracks created by vessels within a length range centred around the length of the vessel being sampled for. If insufficient tracks are available to draw the desired size of sample, the length search bounds are recursively expanded until a sufficient number of tracks are available.

While it intuitively seems appealing to sample of tracks from the group of tracks produced by vessels that are most similar in length to the vessel in question, this has some potential issues. The data available about vessels that produced AIS tracks is entered by the user of the AIS device and, therefore, can be inaccurate. It may also be unreasonable to treat vessel length as a proxy for activity. Therefore, it could be advantageous to search more broadly around the vessels length so that it has a less significant influence on the sample selected, or to discard length entirely as a factor used when sampling.

The number of AIS tracks used to represent the activity of each vessel is a significant variable. One approach is to select a single track and treat that as the activity profile for the vessel. Of course, there is a risk that the track selected has an unusual activity profile, which, in reality, would reflect the activity of few vessels well. This could result in a significant level of bias in results if the track happened to be selected to represent the activity of a large number of vessels, resulting in the unusual activity profile being overrepresented in results. The risk of this can be reduced by sampling multiple tracks for each vessel and taking an average of the emissions calculated for them. However, it is still possible for certain tracks will be sampled much more frequently than others, leading to their overrepresentation within the resulting emissions inventory. Of course, another option is to sample a single track for each vessel but run the model multiple times with different random track samples and to either average the results of the emissions inventory as a whole or to use the range of results to estimate uncertainty (this approach is used in Chapter 5).

It is likely that this interplay between the strictness of the initial length bounds used for vessel sampling and the number of tracks sampled for each vessel will have a significant influence on the sample selected. In particular, the risk of overrepresentation of a small subset of certain AIS tracks in the overall emissions inventory is something to be avoided.

In this chapter, an in-depth analysis of the influence of using different sampling policies on the sample selected will be presented. Conclusions will also be drawn about the appropriate sampling approach for calculating the emissions caused by the case study fleet of UK fishing vessels.

A number of different analyses were undertaken to understand, test and inform the selection of an activity sampling approach. To improve coherence of the chapter, the methodology, results and discussion of each different analysis are presented as one subsection each.

4.2 Methodology overview

A range of approaches were used to assess the properties of the samples selected when varying the criteria used during selection. A number of tests were also performed to test the assumptions used for filtering and using length for sampling.

To assess the quality and similarity of the vessel length data contained in the European Commission Community Fishing Fleet Register (ECCFFR) (EC, 2013a) and the data from MarineTraffic.com (2013) the two datasets were compared graphically and statistically. These are the data that would be used for the potential stratification of sampling based on length so it was important to assess their quality.

The assumption that length is a meaningful piece of information for use in sample was also tested. The vessel length data accessed through the *MarineTraffic.com* (2013) website was tested for correlation with a variety of performance characteristics. Correlation would indicate that vessels of different lengths have different activity profiles. For example, larger vessels may be more active than smaller vessels or vice versa. If this were the case, it would indicate that restricting the potential sampling pool of tracks for each vessel based on vessel length would increase the likelihood of matching vessels to AIS tracks that are representative of their activity than purely random sampling. If no relationship between length and activity is found, using length as a basis for sampling would serve little purpose and could introduce unwanted bias to results.

The effect of varying the filtering parameters on the number of valid tracks available for sampling was also assessed. Selecting the filtering criteria is a trade-off between improving the quality of the sampling pool and reducing the number of AIS tracks available for samplings and, potentially, introducing some unintended bias such as selecting tracks produced by more active vessels.

A detailed assessment of the number and frequency of tracks sampled was made for a range of different track sample sizes between 1 and 50 tracks per vessel. The effect of varying the initial search bounds around the vessel's length when using stratified sampling based on vessel length was also tested. Initial length bounds were varied from ±0 to ±25 metres. An unbounded search, where vessel length was not used to stratify the sample size was also included for comparison.

4.3 Length comparison

Vessels were grouped into length categories, based on their length rounded to the nearest metre. Summary statistics were calculated for each vessel length dataset and an independent-sample *t*-test was undertaken to assess the significance of the difference between the datasets.

The independent-sample *t*-test is used to compare two sets of numerical data to determine whether they are significantly different from one another. For example, the independent-sample *t*-test could be used to determine whether there is a significant difference in the heights of people from two populations based on a random sample of heights taken from each. There will almost certainly be some difference in the means of the two height datasets but also a degree of overlap when looking at the distribution of sampled heights. The independent-sample *t*-test provides a statistical test to determine the probability (p) that the observed differences are an artefact of sampling given the means, variance and number of sampled data points. If the probability that the observed difference is an artefact of sampling is low, it can be inferred that there are significant differences in the underlying populations. The formula for the independent-sample t-test is reproduced in Equation 4.1, after Field et al. (2012).

$$t = \frac{\overline{X_1} - \overline{X_2}}{\sqrt{\frac{s_p^2}{n_1} + \frac{s_p^2}{n_2}}} \qquad \text{Eq. 4.1}$$

$$s_p^2 = \frac{(n_1 - 1)s_1^2 + (n_2 - 1)s_2^2}{df}$$

$$df = n_1 + n_2 - 2$$

Where:

t = the t-statistic, which can be looked up in t-statistic tables using the degrees of freedom (df) to find the probability (p) that the observed difference is an artefact of sampling, e.g. t-statistic tables presented by Friend et al. (2012).

$\bar{X}$ = mean of a sample population.

s = standard deviation of a sample population.

df = degrees of freedom

n = number of samples taken from a population.

Figure 4.1 shows the percentage of tracks for each vessel length set within length groups. It is clear that the two datasets have quite a different spread of vessel lengths. The lengths from the ECCFFR database (EC, 2013a) have a mean of 9.53 m with a standard deviation of ±6.96 m. The lengths obtained from the *MarineTraffic.com* website (MT) have a mean of 23.92 m with a standard deviation of ±21.79 m.

Running an independent-sample t-test reveals that there is a very significant difference between the two length datasets ($t = 49.89$, $p < 0.001$, $df = 11{,}610$). The *MarineTraffic.com* AIS vessel data also have a significant number of outliers, with 396 of the vessels of length 0 m and 46 having a length greater than 100 m and 6 have a length greater than 150 m. By comparison, the ECCFFR dataset (EC, 2013a) contains no vessels with a length under 1 m and only 1 vessel with a length in excess of 100 m.

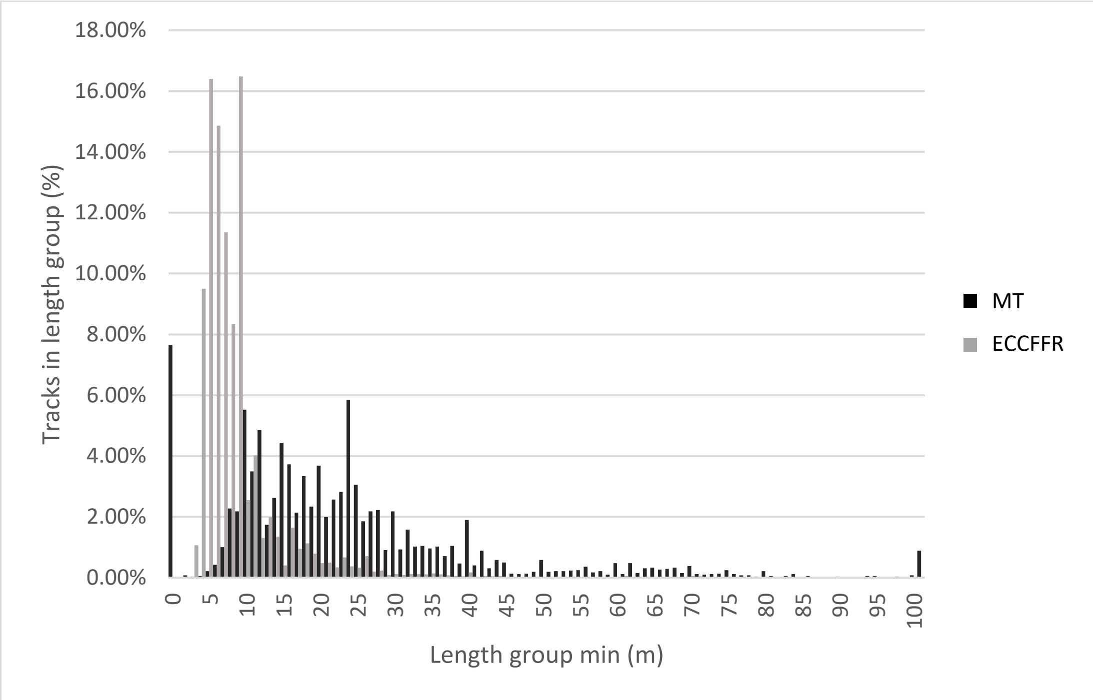

Figure 4.1. Comparison of lengths from the MarineTraffic.com AIS vessel data and the EC Community Fishing Fleet Register (ECCFFR) database (EC, 2013a).

The results of this analysis suggest two important things. Firstly, that the AIS length data obtained from the *MarineTraffic.com* website are likely to contain a significant proportion of errors. For example, the 396 vessels with a length of zero are likely an indication of the length having not been configured on the AIS transponder. AIS transponders have defaults of 0 m for all vessel dimensions (U.S. Coast Guard Navigation Center, 2017). The large number of lengths greater than 100 m are also likely a result of user error. The overall much higher mean length of the AIS data could be caused by three things. It is likely that AIS devices are more frequently installed on larger fishing vessels. There is also a possibility that some users mistakenly use imperial measurements and therefore have entered their vessel lengths in feet rather than metres. Overall, the lengths in the AIS vessel data appear to be of poor quality, which brings into question whether they should be used in any way for modelling the case study fleet.

4.4 Correlation of length with activity metrics

Length was tested for correlations with three activity statistics, calculated for each AIS track. The activity statistics compared were: 1) the ratio of time a vessel spent moving, 2) the mean relative speed of the whole AIS track, 3) the mean relative speed of the parts of the AIS track where the vessel is moving.

The Spearman's rank correlation test was used. This is a correlation test that can be applied to non-parametric data. Since the data do not appear to be normally distributed, this was selected over the Pearson's correlation coefficient, which should only be applied to parametric data. The Pearson's and Spearman's rank correlation tests are closely related, given that the Spearman's rank correlation test is simply the Pearson's test applied to the *ranks* of the paired data, rather than the data themselves. The formula for calculating the Pearson's (r) correlation coefficient is reproduced in Equation 4.2, after Field et al. (2012). To calculate the Spearman's rank correlation coefficient (r_s), the x any y values for each paired data point are replaced with their corresponding rank (in ascending order). Where multiple instances of the sample value appear in the ranked variables, the median rank is applied to each instance, using a half rank interval when necessary (Field et al., 2012).

$$r = \frac{\sum(x_i - \bar{\bar{x}})(y_i - \bar{\bar{y}})}{(N-1)s_x s_y} \qquad \text{Eq. 4.2}$$

Where:

r = a unitless measure of the strength of correlation.

x = the independent variable.

$\bar{x}$ = the mean of the independent variable values.

y = the dependent variable.

$\bar{y}$ = the mean of the dependent variable values.

i = the *i*th data point.

N = the number of data points.

s = the standard deviation of the values of a variable.

The Spearman's rank correlation coefficient was calculated for length and moving ratio, length and average relative speed, and length and average moving relative speed. Length was treated as the independent variable (*x*) in all cases. As a general rule, the r_s value can be interpreted as follows: 0 to ±0.1 indicates no correlation, ±0.1 to ±0.3 indicates weak correlation, ±0.3 to ±0.5 indicates medium correlation and ±0.5 or greater indicates strong correlation. The sign indicates whether variables are positively or negatively correlated (Field et al., 2012).

A handful of AIS tracks were associated with vessels that had extremely large lengths in the *MarineTraffic.com* (2013) dataset. For example, the maximum vessel length recorded was 766 m. For ease of plotting and to reduce the effect of erroneous length data, only vessels with lengths greater than 0 m and no greater than 150 m were included. Figures 4.2, 4.3 and 4.4 show the results of plotting AIS vessel data length against moving percentage, track average relative speed and track average relative speed whilst moving.

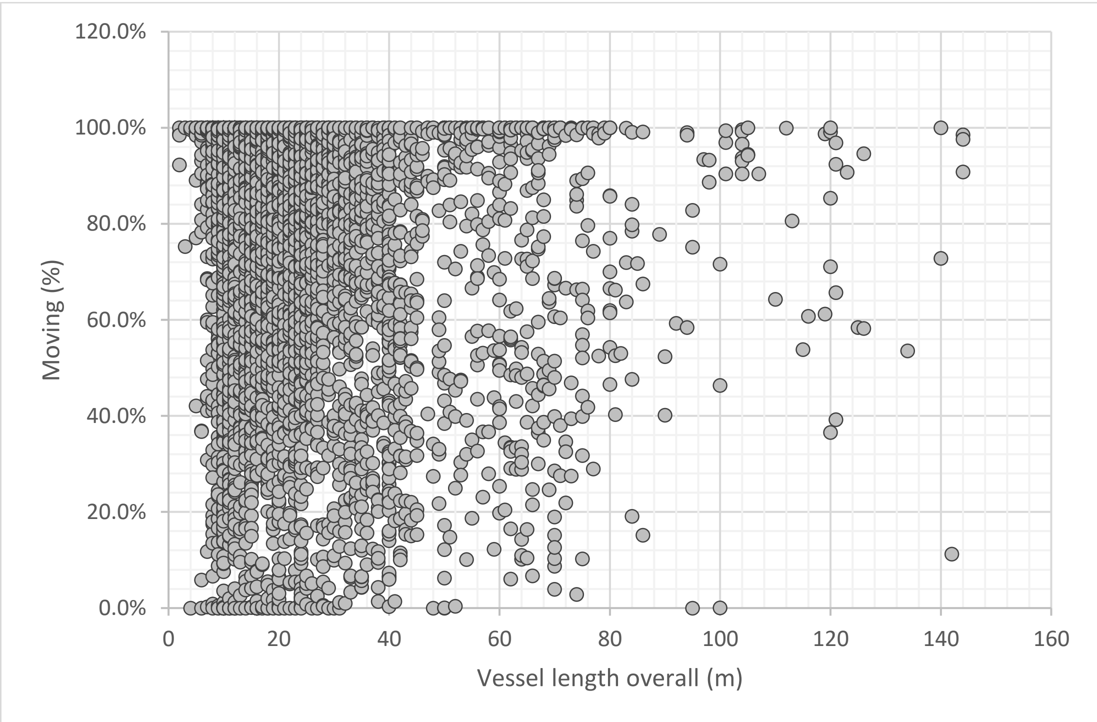

Figure 4.2. AIS vessel data length compared to percentage of the total track that the vessel is moving (speed > 0.05 kmh^{-1}). Spearman's correlation coefficient r_s = -0.094 (n = 4666), showing negligible correlation.

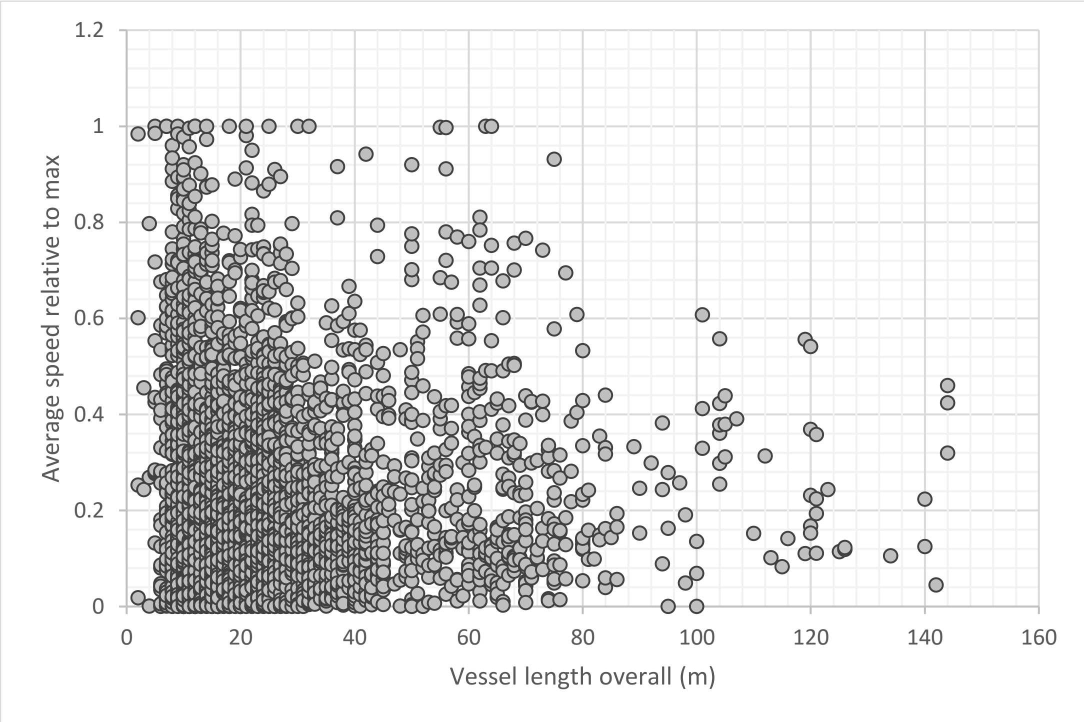

Figure 4.3. AIS vessel data length compared to track average relative speed. Spearman's correlation coefficient r_s = -0.059 (n = 4666), showing negligible correlation.

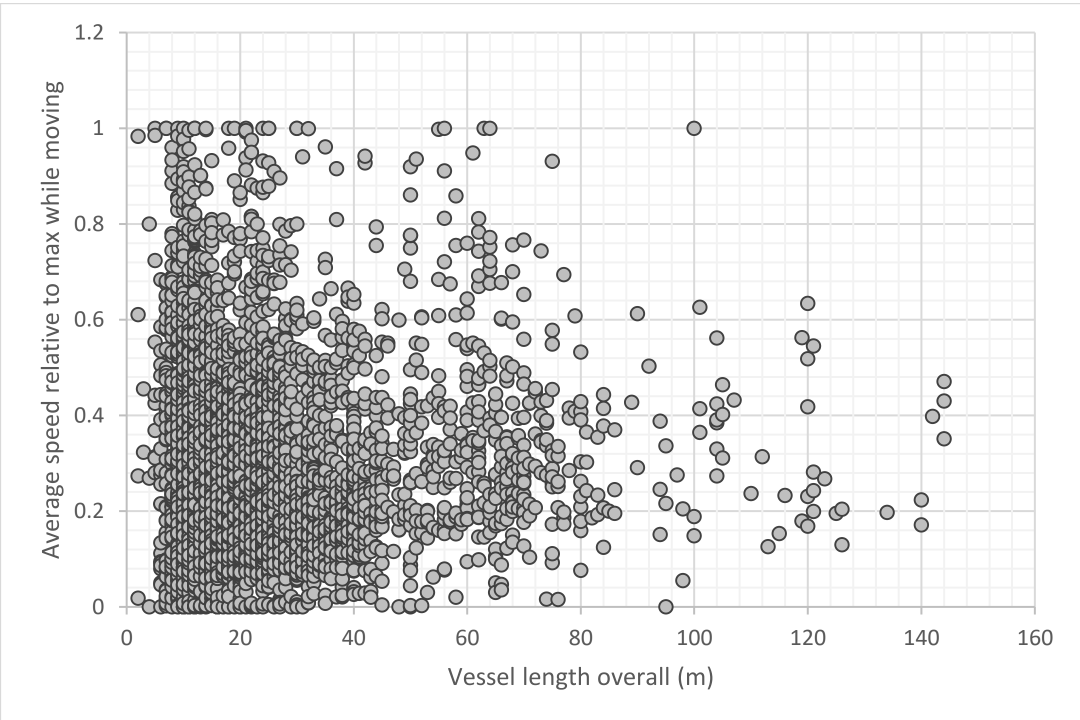

Figure 4.4. AIS vessel data length compared to track average relative speed whilst moving. Spearman's correlation coefficient r_s = -0.030 (n = 4666), showing negligible correlation.

Figures 4.2, 4.3 and 4.4 show no correlation. Length against moving percentage has an r_s value of -0.094. Length against track relative speed has an r_s value of -0.059. Length against track relative speed whilst moving has an r_s value of -0.030. The results of these correlation tests suggest that vessel length is a poor predictor for vessel activity, for this dataset at least. This suggests that there would be little point in using vessel length as a basis for sampling of AIS tracks for vessels that cannot be directly linked with AIS data as there does not appear to be any relationship between vessel length and activity. In fact, the analysis shown in Section 4.6 suggests that using vessel length as a basis for targeted sampling of AIS tracks leads to a significant overrepresentation of certain AIS tracks, leading to biased results.

4.5 Sampling pool sizes

The size of the sampling pool was investigated under increasingly strict filtering criteria in order to find a balance between data quality, specificity to the UK, and the number of tracks available for sampling. This involved altering the minimum permissible number of AIS data points per track, the minimum track duration (elapsed time between first and last AIS data records), and the maximum proportion of track segments with errors (see Section 3.3.5 for an explanation of error detection). This yielded a set of AIS tracks meeting the specified quality criteria.

Tracks were further filtered by the proportion of their port visits that were at ports of a specific country. This yielded a set of AIS tracks that met both the quality criteria and the desired level of specificity to a given country, which is the pool of AIS tracks available for sampling for a vessel belonging to that country's fleet. For the case study dataset, the vessels are all registered as belonging to the UK fishing fleet within the ECCFFR (EC, 2013a). Average metrics (moving percentage, mean relative speed and mean moving relative speed), were also calculated for the tracks associated with different countries in the study area.

The AIS data used for this research comprise 5,178 unique MMSI numbers, each representing a unique vessel and the AIS track that they generated. Of these AIS tracks, 5,061 had at least two AIS data points and so could be processed. A table of results showing the effects of applying different sample filtering criteria is provided in Appendix A. These results show that the filtering constraints used have a profound effect on the number of tracks available for sampling.

For example, constraining this group of AIS tracks to only those containing at least 1,000 AIS data points results in a sampling pool of 3,960 AIS tracks. Applying a minimum total elapsed time between first and last AIS data points of 6 months reduced this pool to 3,373 AIS tracks. Applying a maximum permissible percentage of track segments containing errors of 10% reduced the pool to 3,274 AIS tracks. Applying a much stricter set of constraints, e.g. a minimum of 5,000 AIS data points, 12 months duration and permitting no more than 1% of track segments to have errors reduces the pool size to just 504 tracks.

The application of these filters effectively sets the total number of tracks that are of sufficient quality and contain a sufficient amount of data to be used considered for sampling and use in emissions calculation. Interestingly, when considering the activity metrics calculated, the more restrictive the set of sampling filters applied, the lower the average moving proportion, mean relative speed and mean moving relative speed for the sample. One possible explanation for this could be that applying stricter filtering criteria removes AIS tracks that are generated by vessels that are only observed while moving. This would be the case if their home ports are outside of the study area for which AIS data were available. This would also result in AIS tracks with fewer AIS data points, a short elapsed duration or a high proportion of errors caused by vessels operating outside of network range, leading to track segments with a long duration.

The implication is that relaxing the filtering criteria too far will have the effect of increasing average moving proportion, mean relative speed and mean moving relative speed. This will almost certainly result in an increase in the fuel use and emissions calculated for the case study fleet, which is likely to lead to a degree of overestimation in the resultant emissions inventory. A balance must be struck between gaining a sufficiently high quality set of tracks for emissions calculation and creating so restrictive a sampling pool as to be unrepresentative of the vessel population.

The AIS data used were generated by vessels operating in the area between latitudes 40˚N and 65˚N and longitudes 20˚W and 12˚E between 9th May 2012 and 15th May 2013. Within this area there are ports belonging to twelve countries. Therefore, it is more than likely that only a proportion of tracks belong to the UK fishing fleet and it could lead to flawed results if all tracks were included in emissions calculation. In order to identify the tracks associated with the UK, further refinement of sampling must be carried out by isolating only tracks that visit UK ports.

The AIS tracks can be empirically associated with countries based on the ports that they visit. For example, a vessel that stops at UK ports the majority of the time can almost undoubtedly be correctly categorised as belonging to the UK fleet. In general, the tracks associated with a country can be identified as those that stop at the ports of that country some sufficient number of times or proportion of their total stops.

It is important to note that, based on this definition, AIS tracks could be associated with multiple countries if a threshold of less than 50% is set for association with a country. It could also be the case that an AIS track has no detected port visits, and therefore is not associated with a country. This could occur if vessels detected within the study area belong to fleets of countries outside of the study area and, therefore, only appear in the record when in transit. The minimum proportion of port stops selected to classify a track as being associated with a country is a judgement call that must be made by the modeller. For the purposes of this study, tracks are defined as associated with a country if at least 10% of their port visits are at ports of that country. The value was selected as it is considered to show a reasonably strong association with the target country whilst also yielding a reasonable number of tracks for sampling for the UK fleet. The effect of varying this minimum proportion are presented in Table 4.3 and discussed later in this section.

Table 4.1 shows the results of associating tracks with countries from a group of 3,274 tracks remaining after applying quality filtering criteria as described above. The 3,274 tracks are obtained by filtering for tracks with at least 1,000 AIS data points, 6 months duration and no more than 10% of track segments containing errors. For a track to be associated with a country, at least 10% of its port visits would have to be at the country's ports. Mean activity metrics are also shown for the percentage of the time that the vessel tracks are recorded as moving (speed > 0.05 km h^{-1}), mean relative speed and mean relative speed whilst moving.

Table 4.1 shows that, of the 3,274 valid tracks, 2,679 stopped at ports within the study area. Of those, 653 were associated with the UK. Although only 10% of an AIS track's port visits needed to be at UK ports for the track to be associated with the UK, the actual mean proportion of stops at UK ports of the tracks associated with it was much higher at 78.8%. This suggests that tracks tended to be strongly associated with one country. Therefore, if a track stops at a country at all, it is likely to stop at that country most of the time. Appendix

A contains a detailed table of results for different sampling criteria used to sample AIS tracks for the UK fishing fleet.

Table 4.1. Samples with at least 10% port visits at countries presented with average activity metrics.

			Mean activity metrics		
Countries	**Tracks**	**Port stops at country (%)**	**Moving (%)**	**Relative speed**	**Relative speed (moving)**
All tracks	3274	n/a	71.7%	0.184	0.247
All tracks that stop at ports	2679	100%	70.34	0.175	0.240
Belgium	43	65.7%	70.0%	0.134	0.189
Denmark	464	75.2%	58.3%	0.125	0.208
France	447	89.8%	82.7%	0.189	0.224
Germany	133	67.2%	63.7%	0.122	0.182
Iceland	61	100.0%	70.0%	0.223	0.284
Italy	1	70.0%	60.0%	0.053	0.093
Netherlands	348	84.5%	63.2%	0.110	0.166
Norway	468	88.6%	62.3%	0.225	0.344
Republic of Ireland	261	71.2%	73.2%	0.178	0.239
Spain	329	79.6%	84.6%	0.186	0.216
Sweden	76	72.6%	53.9%	0.085	0.152
UK	653	78.8%	76.3%	0.197	0.253

Table 4.1 also shows there are differences in average activity metrics between the groups of vessels associated with the different countries in the study area. Italy can be disregarded, since only one track is associated with it. Of the remaining countries, moving percentage varied between 53.9% and 84.9%, mean relative speed varied between 0.085 and 0.225 and mean moving relative speed varied between 0.152 and 0.344. This suggests that AIS tracks associated with different countries have significantly different activity characteristics. To test the significance of these differences, the tracks associated with the UK were compared to those associated with other nations using an ensemble of Independent-sample *t*-tests (two-tailed) (Eq. 4.1). The results of these are presented in Table 4.2.

Table 4.2. Comparison of activity metrics of AIS tracks associated with the UK with those of other countries using Independent-sample *t*-test (two-tailed).

	Moving (%)			Avg. relative speed			Avg. moving relative speed		
	t	***df***	***p***	***t***	***df***	***p***	***t***	***df***	***p***
Belgium	1.876	694	0.05 < p < 0.1	3.137	694	0.001 < p < 0.002	3.011	694	0.002 < p < 0.01
Denmark	13.465	1115	p < 0.001	10.033	1115	p < 0.001	5.686	1115	p < 0.001
France	-5.469	1098	p < 0.001	1.170	1098	p < 0.001	3.649	1098	p < 0.001
Germany	6.312	784	p < 0.001	6.352	784	p < 0.001	5.570	784	p < 0.001
Iceland	2.803	712	0.002 < p < 0.01	-1.339	712	0.1 < p < 0.2	-1.577	712	0.1 < p < 0.2
Netherlands	9.012	999	p < 0.001	11.304	999	p < 0.001	10.747	999	p < 0.001
Norway	10.152	1119	p < 0.001	-3.176	1119	p < 0.001	-10.326	1119	p < 0.001
Republic of Ireland	1.990	912	0.02 < p < 0.05	2.155	912	0.01 < p < 0.02	1.486	912	0.1 < p < 0.2
Spain	-6.528	980	p < 0.001	1.415	980	0.1 < p < 0.2	4.208	980	p < 0.001
Sweden	8.411	727	p < 0.001	7.310	727	p < 0.001	6.207	727	p < 0.001

t = t-statistic, which can be used with *df* to look up *p* in t-statistic tables

df = degrees of freedom,

p = probability of samples being from populations with the same underlying activity profiles

In Table 4.2, the *p* value can be interpreted as the probability that the difference in the samples observed for the two populations could be an artefact of sampling randomness rather than a meaningful difference in the activity profiles of the underlying populations. For example, $p < 0.001$ indicates that there is a less than 0.1% probability of the two populations under comparison being statistically similar with respect to the metric being compared. Statisticians regularly consider a value of $p < 0.05$ to indicate a statistically significant difference between two populations (Field et al., 2012). On this basis, Denmark, France, Germany, The Netherlands, Norway, Spain and Sweden are significantly different from the UK with respect to all metrics considered. Belgium, Iceland and the Republic of Ireland appear to be more similar, but are significantly different from the UK with respect to at least on activity metric.

Overall, the results of this ensemble of tests show that the activity metrics of vessels associated with the UK are significantly different from the activity metrics of vessels associated with other countries. This highlights the importance of matching AIS tracks on the basis of association to countries when using an activity sampling approach such as this. If the available sample for a given country is too small, it could be increased by including tracks from countries with activity profiles that are statistically more similar to it. For example, when sampling for a UK emissions inventory, it would be more valid to increase the sample size by including tracks associated with the Republic of Ireland (RoI) than Denmark, France or the Netherlands.

The pool of tracks associated with the UK given the above mentioned quality filtering criteria and a requirement of at least 10% of port stops at UK ports is 653. They have average activity metrics of moving for 76.26% of the time with a mean relative speed of 0.198 and mean moving relative speed of 0.253. However, by filtering for vessels with at least 10% of their port stops at ports of either the UK or the RoI, the number increases to 857 (moving 75.22% of the time, with mean relative speed of 0.192 and mean moving relative speed of 0.250). This shows that, for a minor alteration of activity metrics, the sample pool size could be significantly increased.

Another way of varying the sample pool size is to change the minimum proportion of port stops that must be at ports of the relevant countries for tracks to be included in the sample pool. An example of how this changes the sample pool size and average activity metrics for the UK is shown in Table 4.3.

Table 4.3. Comparison of sampling pool size and activity metrics as a result of varying the minimum proportion of port stops at UK ports for a track to be sampled.

Min port stops (%)	**Tracks**	**Error segments (%)**	**Moving proportion**	**Relative speed**	**Moving relative speed**	**UK port stops (%)**
1%	818	2.20%	73.9%	0.191	0.254	63.8%
5%	723	2.28%	75.1%	0.194	0.254	71.8%
10%	653	2.28%	76.3%	0.198	0.253	78.8%
25%	558	2.26%	77.7%	0.204	0.255	89.5%
50%	504	2.26%	77.5%	0.206	0.257	95.2%
100%	353	2.34%	79.4%	0.216	0.262	100.0%

The number of tracks available for sampling for the UK fishing fleet varies considerably as the minimum proportion of port visits at UK ports required for sampling is varied. The sample size decreases from 818 tracks to 353 tracks as the proportion of port stops at UK ports is increased from 1% to 100%. The risk of filtering by too low a proportion is the inclusion of tracks that are not representative of the target country's fleet activity in the samples used for modelling. The risk of filtering by too high a minimum proportion is that relevant AIS data is lost from the sample pool, and the total sample pool size becomes very small.

The results presented in Table 4.3 indicate that it is not uncommon for vessels to visit the ports of more than one country, so filtering for tracks that exclusively stop at UK ports is not desirable. For the case study fleet, a minimum proportion of 10% of port stops at UK ports was selected. This was considered a reasonable trade off because it yielded a sample pool of 653 AIS tracks, which is approximately a tenth of the size of the fleet being modelled (6434 fishing vessels registered in the UK). It also resulted in a total of almost 80% of ports stops at UK ports, indicating that the AIS tracks were generated by a fleet that, overall, had a strong level of association with the UK.

Notably, varying the proportion of port stops required for association of AIS tracks with the UK had an impact on mean activity metrics. In particular, the average proportion of time that tracks in the sample recorded movement increased from 73.9% to 79.4%, which in turn increased the average relative speed of the vessels by 13%, from 0.191 to 0.216. This indicates that increasing the minimum proportion of port visits required for association with the UK will increase the modelled fuel consumption and emissions of the UK fishing fleet. Of course, this pattern will differ for the fleets of other countries. For example, the same analysis performed for tracks associated with Denmark shows the mean moving proportion falling from 58.3% to 52.5% as the minimum proportion of port stops is increased from 1% to 100%.

4.6 Sampling frequency from filtered sampling pools

The final analysis that was undertaken was to calculate the frequency of individual track sampling for a variety of sampling settings. As an example, the sampling frequency of tracks was calculated for tracks associated with the UK (at least 10% of port visits at UK ports), with a no more than 10% of track segments containing errors, a minimum of 1000 AIS data points and 6 months duration. The number of tracks sampled per vessel was varied from 1 to 50, and the initial length search bounds were expanded around the vessel's length from 0 m to an unbounded search where vessel length was ignored in sampling. Tracks were resampled for each vessel and each sampling approach 200 times and summary statistics were calculated.

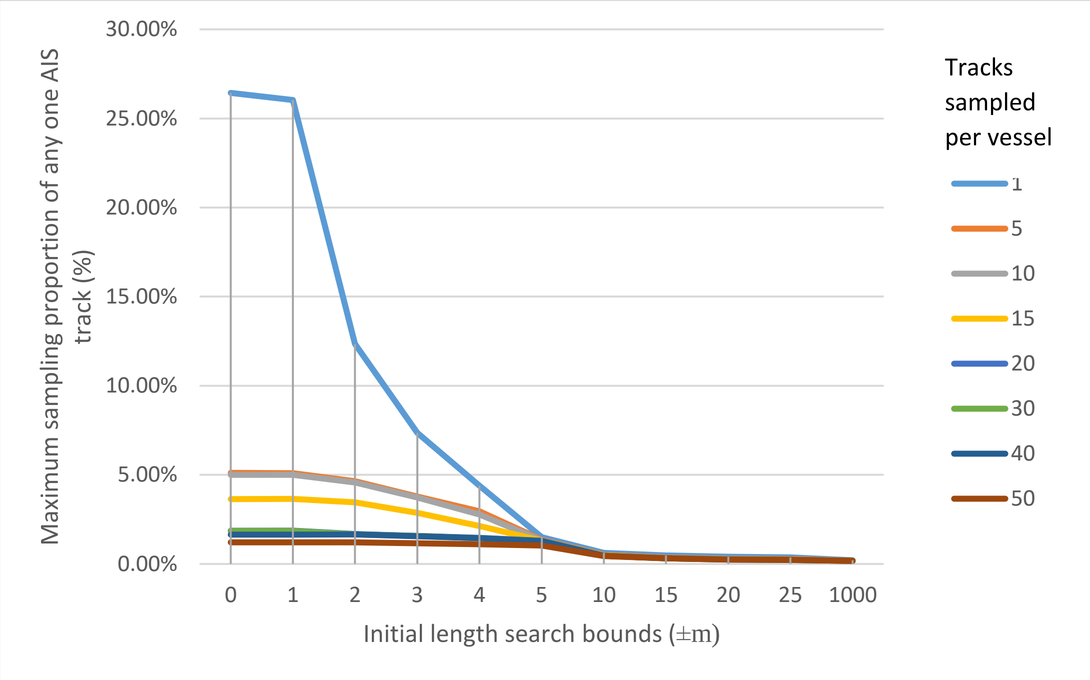

Figure 4.5. The maximum percentage of any track being selected as part of vessel samples under varying sample sizes (number of tracks sampled per vessel) and initial length search bounds.

Figure 4.5 shows the results of this analysis. It was found that, when sampling just one track per vessel and focusing the initial length search criteria strictly to AIS tracks with reported vessel lengths similar to the length of the vessel being sampled for, the most frequently sampled track was sampled 26.4% of the time. This means that one AIS track, produced by a single vessel, was used as the activity data to calculate emissions for over a quarter of the 6434 vessels in the UK fishing fleet. This is a huge bias that would have serious implications for the validity of the emissions inventory calculated as results would be strongly biased towards the specific activity of that one track. If the track happened to be unusual, then the results could be significantly skewed. Further inspection reveals that, of the 653 valid AIS tracks associated with the UK, an average of only 410 (62.8%) were sampled at all in this scenario. This highlights the potential pitfalls of selecting poor sampling criteria when using an activity-sampling approach such as the one described.

At the other end of the spectrum, ignoring vessel length entirely when sampling resulted in essentially no bias, with no track being sampled more than 0.21% of the time and all 653 tracks being sampled multiple times. This held true regardless of the number of tracks being sampled for each vessel.

These results also show that increasing the number of tracks sampled per vessel greatly reduces the extent of the possible bias towards particular tracks being overrepresented in the emissions inventory. However, the reduction in the extent of the bias plateaus at a sample size of 20 tracks (see Figure 4.5), with remaining reductions coming predominantly as a result of increasing the range of the initial length search bounds.

A sample size of 30 could be legitimately selected on the basis of the *Central Limit Theorem*, which shows the likelihood of the mean of a sample falling within a certain margin of error of the population mean for variables that are normally distributed. A sample size of 30 gives a margin of error of less than ±20% with a 95% confidence level (Burt & Barber, 1996).

4.7 Conclusions

The analyses undertaken into the effect of various sampling criteria reveal a number of findings: 1) The lengths available from AIS data are of poor quality. 2) Length is not a good predictor for vessel activity. 3) The number of AIS tracks available for sampling varies greatly depending on the filtering criteria applied for data quality. 4) Track data quality filtering has a significant impact on activity metrics. 5) The AIS tracks associated with different countries have significantly different activity metrics. 6) Sampling an insufficient number of AIS tracks for each vessel or stratifying samples too strictly by vessel length can introduce significant bias with certain AIS tracks being hugely overrepresented in the emissions inventory.

The sampling criteria selected can clearly have a considerable influence on the emissions inventory calculated. Therefore, careful consideration must be given to the samples selected when applying different criteria. The methods outlined in this chapter go some way toward enabling the selection of an appropriate sampling approach.

Given the effect of filtering based on quality criteria and by country association, it is recommended that the quality filtering criteria applied should be for at least 1000 AIS data points, ½ year duration and no more than 10% of track segments containing errors. These values are suggested for the particular AIS dataset under analysis for the case study as they strike a balance between removing tracks with extremely limited data or a high proportion of errors and retaining a sufficient number of tracks to represent the activity of the UK fishing fleet.

The results presented in Section 4.5 imply that there are significant differences between the activity profiles of the fleets associated with different countries (Table 4.2). Therefore, tracks should be filtered for relevance to fleets of the countries being modelled. Table 4.3 shows the effect of filtering AIS tracks based on the proportion of their port stops at UK ports. There is a trade-off between the strength of the association with the UK, as defined by the proportion of port stops on the AIS track at UK ports, and reducing sample size. It is also unrealistic to model UK fishing vessels as only stopping at UK ports as the results of the analysis presented in Table 4.3 suggest that it is not uncommon for vessels to visit the ports of multiple countries. Selecting the 10% limit for the minimum proportion of port stops at UK ports seems to strike a balance between sample pool size and association with the target country, with the filtered AIS tracks showing an average of almost 80% port visits to UK ports.

Applying these filtering criteria reduced the sample pool size to 653 AIS tracks, which is an activity sample of 10.1% of the 6434 vessels in the case study vessel characteristics database. This provides a larger activity sample than previously published research that has used vessel operator surveys (e.g. Psaraftis & Kontovas, 2009), but will clearly yield results with a greater level of uncertainty than AIS-based approaches that rely on accurate matching of each vessel with its AIS track.

The analysis undertaken in Section 4.6 and displayed graphically in Figure 4.5 suggests that significant sampling bias can be introduced by using strict length stratification in sampling, with some AIS tracks being overrepresented in results. The analysis conducted in Section 4.3 also suggests that vessel length in AIS data is unreliable, and the lack of correlation with activity metrics indicates that length is a poor predictor of vessel activity (Section 4.4). For these reasons, it is suggested that length should not be used as a basis for stratified sampling of AIS tracks.

The variation in the degree to which tracks are represented in the activity samples selected also reduces as the number of tracks sampled for each vessel increases. It is suggested that a minimum sample size of 20 tracks is used to reduce the potential for bias in the aggregate sample selected for all vessels. Beyond a sample size of 20 tracks, there appear to be diminishing returns in terms of improving the evenness of representation of tracks sampled. However, increasing sample size may be desirable to improve the robustness of results for individual vessels. For example, a sample size of 30 tracks could be seem as desirable on the basis of the *Central Limit Theorem*.

5 Uncertainty and sensitivity associated with AIS-based emissions inventories for small commercial vessels

The purpose of this chapter is to provide an in-depth analysis of the sources of uncertainty that affect the methodology for modelling fuel use and atmospheric pollution emissions from small commercial watercraft presented in Chapters 3 and 4. A sensitivity analysis is carried out using the data for the case study fleet of UK fishing vessels, which sheds light on the sensitivity of results to the of various input parameters that are subject to uncertainty. An uncertainty analysis is also undertaken, providing an estimate of the overall uncertainty in the results calculated. The findings of this chapter also inform the calibration of input parameters for the model of the case study fleet, the results of which are presented in Chapter 6. This chapter satisfied objective 3:

> *"To identify sources of uncertainty that affect the emissions calculation methodology developed and undertake a rigorous sensitivity and uncertainty analysis."*

5.1 Introduction

Sensitivity analysis is a process of understanding the significance of uncertainty or variation in model input parameters to the model output. Uncertainty analysis is a related but different process of quantifying the range of possible model outputs, given inputs with a degree of uncertainty (Saltelli et al., 2008b).

There are various techniques that can be employed when conducting a sensitivity analysis. Local sensitivity analysis involves changing input parameters in relation to their baseline values to determine the influence that this has upon the results of the model. This does not necessarily capture the full range of values that an input parameter can take, but does provide useful information about the change in results caused by the perturbation of an input parameter. Global sensitivity analysis involves assessing the sensitivity of results as input parameters are varied within a probability distribution used to represent the entire range of their possible values (Hamby, 1995).

The sophistication of techniques also varies from those that consider only changes in a single parameter at a time to those that vary multiple parameters at once. Varying multiple parameters at once has the advantage of allowing modellers to identify potentially complex interactions between parameters (Campolongo et al., 2007; Saltelli et al., 2008a). The simplest approaches are those that consider changes to input parameters one-at-a-time (OAT), and for models with relatively simple dynamics, this is usually sufficient to capture the sensitivity of the model (Saltelli et al., 2008a).

When the probability distributions of input parameters are not known, local perturbation methods can be used to gain a sense of the sensitivity of model results to variation of these parameters. The value of these input parameters can be varied within a range, e.g. ±10% of the default value, to quantify the effect on results (Hamby, 1995).

For input parameters that can be described with a probability distribution, global sensitivity analysis can be carried out using this distribution for a more thorough exploration of the parameter’s range of effects on results. One such technique is the sensitivity index, which is a simple measure of the variation in model outputs when an input parameter is varied through its full range of values (Hamby, 1995). Monte Carlo techniques involving repeated random sampling of input parameters can also be used, but are computationally inefficient and are not guaranteed to explore the full range of an input parameter represented with a continuous probability distribution.

For parameters that cannot be described with a continuous probability distributions, e.g. parameters represented by discrete input parameters, the variance of outputs as a result of changes in the input sample can be quantified using Monte Carlo simulation (Sobol, 2001). Descriptive statistics can be calculated to quantify and compare the variation in results caused by different input parameters.

Within the literature on shipping emissions inventorying methods, Jalkanen et al. (2014) consider the various sources of uncertainty associated with model inputs. These can be grouped into four categories: 1) AIS data quality issues, 2) incomplete vessel technical data, 3) errors in engine load calculation, 4) limited data for emission factors and fuel characteristics.

The most significant of the sources of uncertainty are estimated to be major temporal and geographic coverage gaps in the AIS data record and uncertainties arising from errors in engine load calculation. Uncertainty around operating conditions is also significant. One of the major factors involved in this is the effect of sea ice, an issue of far more relevance in the Baltic Sea than around the coast of the UK. The effects of wind, waves and tidal currents are also a notable source of uncertainty. Furthermore, the application of emission factors to older vessels is identified as a potential cause of underestimates of NO_x emissions and uncertainties surrounding fuel composition give rise to considerable uncertainty in the calculation of SO_2 and particulate emissions.

The *IMO Third GHG Study* (Smith et al., 2014) uses the uncertainty classification produced by Jalkanen at al. (2014) to inform their assessment of the uncertainty of the emissions inventory calculated. In addition, the uncertainty associated with the difference between speed over ground (SOG) and speed through the water (STW) is considered. This difference arises because AIS data contain SOG derived from GPS systems; yet a vessel may be moving at a different STW due to currents such as tides. A dataset for a small fleet of vessels containing measurements of both SOG and STW is used to calculate statistics describing the average difference between the two. This reveals that the mean difference is relatively small at -0.14 knots (SOG-STW), but that the standard deviation is relatively large at ±0.95 knots.

Given that fishing vessels regularly cruise at around 9 knots (Laurens et al., 2013), the mean difference of -0.14 knots is relative small. For example, if a vessel's SOG was recorded as 9 knots, the mean STW is expected to be approximately 9.14 knots (+1.6%). Assuming a design speed of 10 knots, sea margin of 10% and idling engine load of 20% and using Equation 3.6 to calculate engine load, this would result in a small but not insignificant increase in estimated mean engine load of 3.4%. At plus or minus one standard deviation the STW could range between 8.05 and 9.95 knots (±11%), in which case the impact on estimated engine load becomes quite significant, ranging from -20% to +25%. However, assuming the error is normally distributed, these errors can be expected to largely cancel out. The overall impact is likely to be a small underestimate of fuel use and emissions of around 3%.

Smith et al. (2014) also highlight that the relationship between the uncertainties in inputs and results is often complex and non-linear. Therefore, Monte Carlo techniques should be used to compute emissions inventories with a realistic quantification of uncertainty.

In this chapter, the results of a sensitivity analysis are presented and model parameters are ranked in terms of their importance. Monte Carlo simulation was also undertaken to quantify the uncertainty of the model.

5.2 Sources of uncertainty

The results of this study were subject to uncertainty in a variety of input parameters. The variables that affect the model include emission factors, vessel characteristics and the parameters used for engine load calculation. A full list of sources of uncertainty is provided in Table 5.2. Incompleteness of activity recorded in the AIS dataset is another important source of uncertainty. In addition, the methodology used in this research also introduces the additional uncertainty that comes from using an activity sampling approach to match vessels within the modelled fleet to that AIS tracks that provide the activity data. This was a necessity given that the data required for directly linking vessels in the vessel database to AIS tracks was unavailable. Also, a large proportion of the fleet were not represented in the AIS data record that can still be modelled using the approach presented in this research.

Other shipping emissions inventories have also used vessel specific information on the fuel and engine types used (Smith et al., 2014). In contrast, this research relies on published data on the proportion of fishing vessels in the global fleet using the various engine and fuel types used. Therefore, there is some uncertainty related to their applicability to individual vessels, the impact of which should also be estimated.

The emission factors used in this research were taken from the *EMEP/EEA air pollutant emission inventory guidebook 2016* (Trozzi et al., 2016). Uncertainty ranges are given for emission factors (reproduced in Table 5.1), estimated at the 95% confidence level. No advice is given about an appropriate probability density function with which to represent these range values. Given that the emission factor ranges are large, they were expected to be a significant contributing factor to the overall uncertainty of the results.

Table 5.1. Estimated emission factor uncertainties at the 95% confidence interval (after Trozzi et al., 2016)

Parameter	At sea	Manoeuvring	In Port
NOx	±20%	±40%	±30%
SOx	±10%	±30%	±20%
NMVOC	±25%	±50%	±40%
PM	±25%	±50%	±40%
Fuel consumption	±10%	±30%	±20%

The uncertainty associated with the incompleteness of AIS data is difficult to quantify. The emissions calculation methodology presented includes functionality for the detection of large gaps in AIS tracks and unrealistically high speeds, which are also thought to be indicative of errors in the data. In these cases, average activity data are applied which are derived from the rest of the AIS track. Tracks with a particularly high proportion of errors are filtered from the pool of AIS tracks that are available for sampling. In addition, AIS tracks are filtered to exclude tracks that contain extremely low numbers of AIS data points and that are only active briefly within the complete time for which emissions are modelled. These measures were taken to reduce the error and uncertainty caused by poor AIS data quality. However, quantifying the uncertainty associated with AIS data quality was not undertaken given the lack of data required to reliably assess its impact.

The owners of all fishing vessels licenced to EC member states are legally required to keep the information about their vessel up to date in the ECCFFR (EC, 2013a). This was considered a high-quality source of vessel characteristics data. Inspection revealed that the data for each vessel in the database were complete and did not have obviously erroneous values. As such, the data taken from this database was assumed to be complete and correct. However, the database did not contain all of the information required as inputs for emissions calculation. Specifically, the vessel engine, fuel type and design speed were not included. The engine and fuel type are used to select emissions factors for emissions calculation. The design speed is an important piece of data used in engine load calculation. As such, alternative sources of these data were required.

Given the lack of engine and fuel type in the vessel technical data available, fleet level averages for fishing vessels were used. These were taken from the *EMEP/EEA air pollutant emission inventory guidebook 2016* (Trozzi et al., 2016). These data are not specific to the UK fishing fleet and so it is likely that there is some discrepancy between the fleet averages applied and the real vales for the fleet being modelled. There is also uncertainty around the selection of an engine and fuel type for each vessel. Either a weighted average of all possible engine and fuel type combinations can be used, or the fleet level data can be used to create a discrete probability distribution from which engine and fuel types can be sampled for each vessel.

In lieu of vessel design speed data, the AIS data were used directly to estimate vessel design speed. This was calculated as the maximum speed maintained for some cumulative duration. For example, if at least X mins of a track had a speed of Y or greater, Y could be taken as a proxy for design speed. The entirety of each AIS track was used to estimate design speed in this way. Of course, the cumulative duration used for deriving maximum speed influences the speed derived, with higher durations leading to lower maximum speeds and vice versa. Any duration greater than zero and below a relatively large value, e.g. an hour, could legitimately be chosen.

Modelling main engine load from speed has a few areas of uncertainty. The method used for modelling engine load (Eq. 3.6) uses instantaneous speed, design speed, idling/hotelling load and sea margin to calculate load. There is differing advice in the literature about both hotelling/idling loads (MARIN, 2012; Trozzi et al., 2016) and sea margins (Buhaug et al., 2009; Lindstad et al., 2011; Smith et al., 2013). Smith et al. (2013) highlight the importance of sea margin in emissions calculation. Therefore, uncertainty in the parameterisation of the engine calculation formula will give rise to uncertainty in model results.

When designing ships, sea margin is an additional provision of engine power, usually of between 10% and 25%, intended to enable ships to overcome additional resistance from wind, waves, fouling, etc. in order to maintain design speed in the majority of conditions (Wärtsilä, 2018). In practice, this means that a ship operating at design speed in calm water with minimal resistance will have an engine load of 100% minus the sea margin. In operation, the resistance that the ship is working to overcome is usually considerably less than that allowed for by the sea margin, so the engine load must be adjusted downwards by an appropriate amount when modelling it from an approximate relationship to speed.

Speed is calculated over ground rather than through the water. The movement of water due to tides and currents is not modelled. If vessels move without consideration for currents, the net effect should be approximately zero. However, there is an economic driver to move with currents where possible to reduce fuel costs. Moving with the current would effectively reduce speed through the water for the same speed over ground, resulting in lower engine load, fuel use and emissions. On the other hand, moving against the current and, therefore, faster through the water has a greater impact on fuel consumption and emissions than reducing speed, given that the relationship between speed and engine load is approximately cubic (Jalkanen et al., 2014). Quantifying the difference between SOG and STW was not possible with the available data. However, analysis carried out by Smith et al. (2014) suggests that the net effect is likely to be minor.

A number of methods were trialled for the calculation of AIS track segment instantaneous speeds. These were: 1) applying the average of the speeds contained in the two AIS data points describing a track segment; 2) using distance and duration of segments to calculate speed; 3) using distance and duration, but smoothing results by calculation average speed for groups of segments of some minimum total duration; 4) a combination of 1 and 2, where the distance-based speed is treated as logical lower bound and AIS average speed is used as an upper bound, if higher; 5) a combination of 1 and 3 calculated in the same way. This gives rise to some structural uncertainty about the methodology used and the speed calculation approach that yields the best results.

The use of a combined speed methodology produces an upper and lower speed over ground for each AIS track segment. This range can be treated as a probabilistic input to engine load calculations. This also applies to derived maximum speed, which also has a lower and upper range value as a result of using a combined speed calculation approach.

Associated to speed calculation, a minimum speed is used to determine when a vessel is moving. This is important in order to prevent modelling very slow movement as an indicator of engine activity, where it is far more likely to be a result of instrumentation error or vessels drifting whilst moored or at anchor. Determining a reasonable value for this is important to model emissions well and a poorly selected value will cause errors.

The methodology presented also models engines running before and after journeys while the vessel is stopped. There is some advice on modelling this in Trozzi et al. (2016), which suggests main engines run for approximately 5% of the duration of stops for all vessel types other than tankers. However, it is not explicitly stated whether this advice is applicable to small commercial vessels. Therefore, this is another source of uncertainty contributing to the calculated of engine load.

Engine load override rules are also used to apply a trawling or dredging engine load to fishing vessels when their activity data suggests that they are engaged in these activities. The use of engine load override rules is novel to this research. The effect of using these engine load override rules is quantified to determine their importance to results.

A final source of uncertainty that is worth mentioning is the accuracy of the GPS used by the AIS equipment. Modern, purpose GPS devices have an accuracy of ≤ 0.715 metres at confidence level of 95% (GPS.gov, 2017). This means that the location of a vessel should be within 1 metre of the location reported in each position message for a large majority of measurements. This error is likely to be symmetrical about the ‘real’ location of the vessel’s GPS device with a mean error for all position messages of close to zero. The effect of GPS errors could result in minor inaccuracies in the speeds calculated for AIS track segments. However, by smoothing speeds for track segment groups, the impact of these potential errors is reduced. Overall, the uncertainty associated with GPS inaccuracies is considered to be minor and is not modelled.

Sources of uncertainty can be categorized as aleatory (intrinsic but modellable with available data) or epistemic (reducible by gathering additional data) (He et al., 2015). There are also structural uncertainties about the methods used. Table 5.2 contains a summary of the sources of uncertainty modelled in this analysis. Importantly, both aleatory and epistemic uncertainty can be modelled in uncertainty and sensitivity analysis provided that sufficient data are available to describe probability distributions to represent the uncertain inputs. Structural uncertainty can be assessed by running the model with the application of the different methodologies under investigation.

Table 5.2. Sources of uncertainty, categorized as either structural, aleatory or epistemic.

Source	Type	Comments
Emission factors	Aleatory	Given the relatively large ranges of uncertainty associated with the emission factors used, these will contribute significantly to the uncertainty in the results.
AIS data quality and gaps	Epistemic	The methodology used filters out low quality tracks and attempts to mitigate the influence of errors in the remaining data. However, access to additional AIS data, particularly satellite AIS data, would reduce the uncertainty considerably.
Engine load estimation	Epistemic / aleatory	Obtaining data on the design speed of the vessels being modelled would reduce uncertainty. Without this data, some analysis can be performed to understand the sensitivity of results to the parameters used to convert speed to engine load.
Track sampling	Epistemic / aleatory	If data were obtained that allowed vessels and AIS tracks to be linked, this would reduce uncertainty. Where vessels and tracks cannot be directly matched,

Source	Type	Comments
		this can be seen as aleatory uncertainty that can be quantified by running multiple runs with different random samples. However, it could be eliminated as a source of uncertainty if the data necessary to match vessels to AIS data were made available.
Instantaneous vessel speed	Aleatory	The use of a combined instantaneous speed calculation methodology gives lower and upper bounds for the instantaneous speed of track segments. This can be used to construct a probability distribution of the speeds for each AIS track segment.
Vessel engine and fuel type	Epistemic / aleatory	Given that vessel and fuel type proportions used by fishing vessels are available in the literature. This can be treated as an aleatory source of uncertainty by randomly selecting engine/fuel type using the proportions provided in the literature. However, gathering more information on the specific engine and fuel types used by individual vessels would eliminate this uncertainty.
Main and auxiliary engine running times whilst hotelling	Epistemic / aleatory	More information on the running of engines used aboard fishing vessels whilst hotelling would reduce this uncertainty. However, this can be reasonably modelled as between zero and the default values used.
Speed calculation method	Structural	Three speed calculation methods were proposed and trialled in this research. There is uncertainty as to which produces the most realistic results.
Engine load override rules	Structural	A new concept of engine load override rules has been introduced to model trawling and dredging engine loads. The significance of these rules can be assessed by modelling emissions with and without engine load override rules.

5.3 Methodology

Sensitivity and uncertainty analysis requires a model to be run many times to explore the impact that uncertain inputs have on results. The first version of the modelling software was computationally inefficient, with each model run taking around 3.5 days to complete for the UK fishing fleet dataset. This made it impractical to run meaningful uncertainty or sensitivity analysis given that the number of runs required would have taken years to complete. Therefore, for uncertainty and sensitivity analysis to be carried out, the modelling software needed to be optimized to significantly reduce run times. The optimizations made to the software are summarized in Section 5.3.1.

With the optimized software, a sensitivity analysis was undertaken to better understand the influence of various methodological choices and uncertainty associated with input data. The specific sensitivity analyses undertaken are introduced in more detail in Section 5.3.2. Finally, Monte Carlo simulation was undertaken to perform an uncertainty analysis. A range of potential results were calculated, modelling the uncertainty of several input variables and their effects upon results. The methodology used is outlined in Section 5.3.3.

5.3.1 Optimizing the modelling software

In any computation, some of the most computationally expensive and slow operations are associated with Input-Output (reading and writing data to local or network storage). Given that the software created during this project runs locally, one of the major contributors to model run time is reading data from and writing data to the hard drive. Therefore, the software was engineered to minimise this type of operation.

Additionally, in order to optimize a program written in Java, the specific operations that are expensive in the Java programming language must be considered. Java is an object oriented programming language, which means that data are stored in memory as user defined objects. Once in memory, accessing and manipulating objects can be done extremely quickly and efficiently. Two of the most expensive operations in Java are object creation, where a location in physical memory is assigned to the object, and 'garbage collection', a process where redundant objects are identified and deleted to make the memory that they use available to store other data. Without garbage collection, many memory intensive Java programs would run out of memory and crash.

Java programs are run by a Java Virtual Machine (JVM). The JVM carries out garbage collection automatically so the user does not have to manually delete objects. Generally, this makes it easier to develop software. However, the garbage collection process can be costly if new objects are created at a rapid rate, causing programs to run slowly. Therefore, garbage collection must be considered when optimizing a data intensive Java program. Generally, identifying ways to reduce the number of objects created is the best way to reduce the garbage collection overhead. Therefore, the software was engineered to reduce the number of objects created.

A considerable effort was undertaken to optimize the modelling software tool, with efficiencies being gained in a number of areas. To minimise Input-Output operations, smaller input data files were loaded to memory at the beginning of a model run, e.g. emission factors, vessel databases, vessel type profiles, engine load override rules, ports information, etc. This differed from the original approach which selected data for each vessel from a MySQL database throughout each model run.

The modelling software also does a certain amount of data pre-processing to calculate activity tracks from raw AIS data. This pre-processing includes the calculation of track segment distances, durations and speeds (see Section 3.4) and requires the creation of multiple objects. Once processed, this data can be used repeatedly to calculate emissions for multiple vessels or in multiple modelling runs by the same vessel. Therefore, caching tracks after pre-processing has considerable performance benefits in terms of reduced object instantiations and garbage collection overhead. Of course, this needs to be weighed against memory limitations. Therefore, a maximum cache size was set and tracks were discarded on a least recently used basis. The cache size is effectively limited by the random-access memory (RAM) available on the computer being used to run the modelling software. By increasing the memory available, a greater number of pre-processed tracks could be cached, further accelerating model run time.

The original version of the modelling software used a MySQL database to store all AIS position data indexed by MMSI number. When all AIS data for a particular MMSI (an AIS track) was required, a query was used to select the AIS data associated with that MMSI from the database. Although databases are designed to perform this kind of selection operation quickly, it is not an insignificant computational task to select several thousand rows from a table of many millions. To improve AIS data selection performance, the AIS data were moved out of the database and instead stored in individual files for each unique MMSI number. These files were then loaded directly by the operating system when needed. This greatly optimized the AIS data lookup operations which made up a significant proportion of the overall model run time.

The data processing task naturally lends itself to parallelisation given that the calculation of emissions for each vessel is a stand-alone computation that is not affected by the emissions computed for any other vessel. In computing terms, the task is *embarrassingly parallelizable*, meaning that the data processing operations can be run independently in separate threads of execution with essentially no interaction between the processes beyond the aggregation of results (Vrajitoru, 2017). It was possible to parallelize both the pre-processing of track data and the emissions calculation phases of the model run.

Process parallelization in the software generally followed a master-slave concurrency paradigm used extensively in big data processing (Butcher, 2014). However, the software is designed to run on a single machine rather than on distributed hardware so the masters and slaves were represented by processes running in different threads on the same computer. The computation tasks to be undertaken were created and issued by the master, with each slave processing each task before being issued the next. The master collated the results of all slave processes to produce aggregated results. On the computer used for this modelling, parallelization resulted in almost an eight-fold increase in processing speed given that the computer had eight logical processors. Using a computer with additional cores and enough memory to support the additional data needed in memory, the performance would improve further.

A comprehensive refactoring of the original modelling tool was undertaken with the aim of minimizing computational inefficiencies throughout, eliminating redundant calculations, moving as much logic out of loops as possible and minimizing profligate object instantiations and, therefore, garbage collection overhead. After these changes, which amounted to almost a complete re-write of the original modelling software, a model run could be completed in less than 10 minutes for the UK fishing fleet (assuming a sample of 30 tracks per vessel). The same model run would have taken approximately 3.5 days (~5,000 minutes) to complete with the previous version of the software. This made it feasible to run the software many times, making it possible to perform uncertainty and sensitivity analysis.

The source code for the optimized version of the software is provided in the accompanying electronic material submitted with this thesis. The case study datasets are also provided so that the model can be run and results can be repeated if desired.

5.3.2 Sensitivity analysis methodology

A sensitivity analysis was undertaken to assess the impact of a range of factors on the results calculated. In order to carry out sensitivity analysis, the modelling software was made to run deterministically given a particular set of input parameters. This was necessary so that the effects of parameter changes could be isolated from any inherent randomness in the parameter selection for the Monte Carlo simulation runs. The only aspect of the core software that did not always run deterministically was the track sampling module. This was made deterministic by fixing the random seed, which means that an identical stream of pseudo-random numbers is generated for each run started with any particular random seed. By fixing the seed and ensuring that tracks were sampled for vessels in a predictable order, a repeatable sample of tracks for a given fleet could be generated.

Some areas of the model were subject to structural uncertainty, where different methodologies were trialled to calculate results. The two areas of structural uncertainty were the speed calculation method used and the use of engine load override rules. Results were compared when calculated with all of the different speed calculation methods. The effect of using engine load override rules was also quantified by running the model both with and without engine load override rules.

The software was adapted to accept probabilistic input parameters instead of single value inputs. The probabilistic input parameters represent a range of possible values and are defined by a probability distribution. The parameters that were made probabilistic are listed in Table 5.3. The values of these parameters can be either explicitly set or randomly sampled depending on the run configurations of the modelling tool. When performing sensitivity analysis values are varied through their full range. When carrying out an uncertainty analysis using Monte Carlo simulation, the values of probabilistic parameters are randomly sampled for each run.

Table 5.3. Input parameters and their associated ranges.

Parameter	Range	Baseline
Emission factors	Values from Table 5.1 (after Trozzi et al., 2016)	Modal values
Minimum speed registered as moving	0.000001 (> 0) to 1.0 km h^{-1}	0.05 km h^{-1}
Cumulative duration for derived maximum speed	0 to 60 minutes	20 minutes
Main engine hotelling/idling load	10% to 20% (MARIN, 2012; Trozzi et al., 2016)	20%
Sea margin	5% to 30% (Lindstad et al., 2011; Smith et al., 2012; Trozzi et al., 2016)	10%
Design speed	Track derived, lower and upper bounds from combined speed calculation method	Upper bound
Instantaneous speed	Track derived, lower and upper bounds from combined speed calculation method	Upper bound
Main engine running times when vessel is stopped	Default: 5% of stop duration, min. 30 and max. 120 minutes Range: 0 – 100% of default	Default
Auxiliary engine running times when vessel is stopped	Default:50% of stop duration, min. 120 and max. 1440 minutes Range: 0 – 100% of default	Default

Two simple sensitivity analyses techniques were used. The input parameters were varied OAT. To test the linearity of output response to variation in input parameters, each parameter was run through their full range of values and Pearson's linear correlation coefficient (*r*) was calculated.

Pearson's correlation coefficient (*r*) measures the strength of the linear correlation between two independent numerical variables. The formula for calculating Pearson's correlation coefficient is reproduced in Equation 4.2 (after Field et al., 2012). When testing the significance of a linear correlation, Pearson's correlation coefficient should only be applied to parametric data. However, when used simply to assess the linearity of a relationship this requirement can be relaxed (Field et al., 2012). The correlation coefficient (*r*) ranges between -1 and 1, with values close to 1 indicating a strong positive correlation, and values close to -1 indicating a strong negative correlation. Values close to 0 indicate no correlation in the two variables being compared (UWE, 2018). As a general rule, the *r* value can be interpreted as follows: 0 to ±0.1 indicates no correlation, ±0.1 to ±0.3 indicates weak correlation, ±0.3 to ±0.5 indicates medium correlation and ±0.5 or greater indicates strong correlation (Field et al., 2012).

Having confirmed that all parameters have a strong linear correlation to outputs (see Table 5.4), a local perturbation analysis was undertaken to rank the sensitivity of model results to variation of each input parameter. Each parameter was varied through a range from -10% to +10% of their baseline values (see Table 5.3). A 1% average variation was calculated to provide a normalised percentage variation in results for a 1% variation in each input parameter.

This local perturbation technique does not take into account the full range of values that represent an input parameter. Therefore, the following global perturbation analysis was undertaken for parameters with a probability density function to determine the full range of possible results. The only parameter listed in Table 5.3 that was not included in the global perturbation sensitivity analysis was minimum speed registered as moving. This was excluded because this parameter is an absolute limit set by the modeller to reduce the impact of noisy data and, as such, cannot reasonably be represented with a range of values. Therefore, it was treated separately to identify a reasonable single value to use for further modelling.

Some model parameters could not be described with a continuous probability density function and, therefore, could not be included in the perturbation analyses. Vessel engine and fuel type assignment and the effect of AIS track sampling both share this quality. However, some sense of the sensitivity of model outputs to the uncertainty associated with these inputs can be quantified using Monte Carlo sensitivity analysis, where repeated sampling of input values allows the calculation of statistics about the range of outputs produced.

Vessel engine and fuel type are modelled with proportions taken from the literature (Trozzi et al., 2016) (Table 3.3). The model is usually run with weighted average emission factors generated from these data. However, doing this hides the inherent uncertainties associated with the possible engine and fuel types used by the vessels in the UK fishing fleet. Without additional information, it is not possible to meaningfully model any systematic difference from these fleet level proportions.

However, some sense of the uncertainty associated with engine and fuel type selection can be modelled by treating the fleet level data as a discrete distribution and sampling from it to assign individual vessel engine and fuel type combinations. To quantify this error, the model was run 250 times with engine and fuel types randomly sampled from this discrete distribution for each vessel and model run. This differed from the method used in calculating the baseline, where weighted average emission factors are generated from the same proportions. Using 250 runs was considered a sufficient number to capture most of the variability caused by engine and fuel type selection. If more parameters were being varied, such as for a full uncertainty analysis, a larger number of runs would be required to build up a reasonably accurate picture of the range of possible outputs.

The track sampling methodology is also inherently stochastic and can be seen as sampling from a uniform discrete distribution. To quantify the effect of track sampling, the model was run 250 times with different randomly selected samples of one AIS track per vessel in the fleet.

In order to provide context to these Monte Carlo sensitivity analyses, a similar analysis was also undertaken for emission factors. Emission factor values were sampled for each vessel and run from a triangular probability distribution from the minimum, modal and maximum values in Table 5.1. A total of 250 runs were completed. The results of this can be expected to show less variation than the global sensitivity analysis described above, but serves to provide a basis for assessing the relative sensitivity of results to uncertainty generated by sampling AIS tracks and engine and fuel types.

Unless otherwise specified, the following run settings were used:

- Combined speed calculation method (see below)
- minimum moving speed of 0.05 km h^{-1},
- 20-minute minimum cumulative time for AIS track derived maximum speed,
- a main engine idling/hotelling load of 20% (from Trozzi et al., 2016),

- a sea margin of 10% (from Buhaug et al., 2009),
- main engine running time during stops of 5% of stop duration and between 30 and 120 minutes,
- auxiliary engine running time during stops of 50% of stop duration and between 120 and 1,440 minutes,
- engine load override rules as detailed in Table 3.4.

The default speed calculation method used is the combined method, where the fastest of the speeds taken directly from the AIS data and calculated from distance (for track segment groups of at least 20 minutes total duration) is used. The various speed calculation methods are explained in Section 3.3.5. As recommended in Chapter 4, the track sampling pool was filtered to include only AIS tracks with:

- no more than 10% of track segments containing errors,
- minimum ½ year duration,
- a minimum of 1,000 AIS data points,
- at least 10% of port stops at UK ports

Engine load override rules were used by default. Default error detection settings are used, as described in Chapter 3. Given that analyses are intended for comparison only, a single track sample was used per vessel to reduce model run times.

5.3.3 Uncertainty analysis methodology

An uncertainty analysis was undertaken to quantify the range of possible results output by the model when run with a range of parameter values represented with probability distributions. Monte Carlo simulation was used to sample from the input parameter distributions and repeatedly calculate model results with various combinations of these input parameter. The uncertainty analysis comprised of 2,000 runs of the model with different randomly sampled values for the model input parameters selected for each vessel and run.

Monte Carlo simulation is a simple technique used to explore the join probability distribution of the results of a probabilistic model by running the model many times with different randomly selected values for each probabilistic input parameter. Its main weakness is that it is computationally expensive, since a complete model run has to be computed for each data point in the resulting joint probability distribution. Its strengths are its relative simplicity and ability to deal with both discrete and continuous input parameters and models of an arbitrary level of complexity (Murphy, 2012).

Latin Hypercube Sampling (LHS) was used to improve the results of the Monte Carlo simulation. Latin Hypercube Sampling uses stratification to ensure that probability distributions used to represent input parameters are well represented in sampling. In LHS, instead of fully random sampling for the values of input parameters, the cumulative density function of probabilistic input parameters is split into a range of strata of equal probability and samples are drawn from these strata. The number of strata is usually equal to the number of samples required. The total desired number of samples are drawn by sampling evenly from each of the strata, ensuring that the full range and shape of the input parameter is well represented.

The LHS technique is recommended as a way of reducing the number of model runs required to form a reasonably accurate picture of the join probability distribution of a probabilistic model, using Monte Carlo techniques. It is particularly recommended when dealing with relatively long-running models as a way of reducing the overhead of uncertainty analysis by reducing the number of model runs required to produce reasonable results (Helton & Davis, 2003; Saltelli et al., 2008b; Wu et al, 2013). Because each model run for the case study fleet took a number of seconds to complete and it was impractical to conduct tens of thousands of model runs, LHS was used to improve the veracity of results.

Following sensitivity analysis, the minimum moving speed was changed from the default value of 0.05 km h^{-1} to 0.1 km h^{-1} and was modelled as a fixed value. All other defaults such as for error detection, were retained other than the model parameters discussed below, which were sampled from the probability distributions described.

Emission factors were sampled from a triangular distribution generated from data in the *EMEP/EEA air pollutant emission inventory guidebook 2016* (Trozzi et al., 2016). A single track for each modelled vessel was randomly sampled for each run with equal probability of sampling any track in the filtered sampling pool. Engine and fuel type were selected for main and auxiliary engines from a discrete probability distribution generated with the values in Table 3.3 (Trozzi et al., 2016).

Main engine idling/hotelling load was sampled from a uniform distribution from 10% to 20%. This was based on recommendations from MARIN (2012), where a 10%

idling/hotelling engine load is suggested and Trozzi et al. (2016), where a 20% engine load is suggested. Sea margin was selected from a uniform distribution from 5% to 30% based on data available in the literature (Buhaug et al., 2009, Lindstad et al., 2011; Smith et al., 2012; Trozzi et al., 2016). Main and auxiliary engine running times while hotelling were sampled from a uniformly distributed range from zero to the default values assumed (see Table 5.3).

To represent the uncertainty in vessel design speed, the minimum cumulative duration used to derive maximum speed from the AIS data was represented as a range from 0-60 minutes with uniform probability. The speed ranges generated by using the smoothed hybrid speed calculation method were also treated as uniform distributions, with a point in the range from the lower and upper speeds being randomly sampled for each vessel per run.

The range values used for the input parameters of the uncertainty analysis are generally not balanced around the fixed values used for producing the baseline results. For this reason, systematic deviation from the baseline is to be expected. However, having changed the minimum moving speed from 0.05 km h^{-1} to 0.1 km h^{-1}, the baseline values had to be recalculated. This was done to allow meaningful comparison of the results of the uncertainty analysis with the baseline results. The new baseline was calculated by running the model with 250 different random track samples so that a realistic average baseline value could be calculated.

5.4 Results

The results of the sensitivity and uncertainty analysis are presented below. Given the range of emissions calculated and the need to show results in a digestible format, emission comparison between runs is generally restricted to total CO_2 emissions (sum of main and auxiliary engine emissions). Full results tables are available electronically in the accompanying material.

5.4.1 Sensitivity analysis results

The results of model runs for the UK fishing fleet annual emissions from May 2012 to May 2013 with the different speed calculation methodologies trialled showed considerable variation (Figure 5.1). The smoothed combined speed calculation method produced a baseline result of 1,094.34 kt CO_2 for the UK fishing fleet for the year modelled. The results for the combined, AIS, Haversine and smoothed Haversine speed calculation methodologies were 1,016.31 (-7.9%), 1,264.49 kt CO_2 (+15.5%), 929.18 kt CO_2 (-15.1%) and 1,008.79 kt CO_2 (-7.8%), respectively.

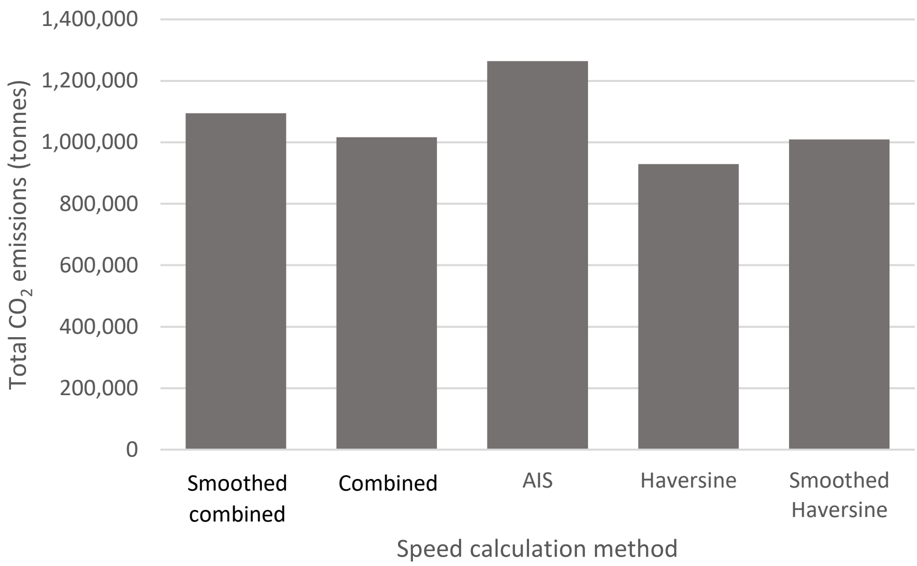

Figure 5.1. Total CO_2 emissions calculated with fixed model parameters other than instantaneous speed calculation methodology.

Running the model without engine load override rules yielded a result of 1,051.52 kt CO_2. This is a relatively minor reduction of 3.9% below the baseline result calculated with engine load override rules.

Cycling through a range of values for the minimum speed to register as moving from 0.000001 km h^{-1} (effectively > 0 km h^{-1}) to 1.0 km h^{-1} resulted in a reducing emissions trend from 1,358.1 kt CO_2 to 1,008.7 kt CO_2 (Figure 5.2). Reducing the minimum speed registered as moving to 0.000001 km h^{-1} yielded results 24.1% higher than the baseline (0.05 km h^{-1}). The difference between the 0.000001 km h^{-1} and 0.05 km h^{-1} was much greater than any of the other differences. Increasing the minimum speed had a smaller effect with 0.1 km h^{-1} giving results that were only 3.9% lower, and 1.0 km h^{-1} giving results of only 7.8% lower than the baseline (0.05 km h^{-1}). The rate of emissions decrease with increasing minimum speed shows a strong linear correlation (r = -0.79) between 0.05 and 1.0 km h^{-1}.

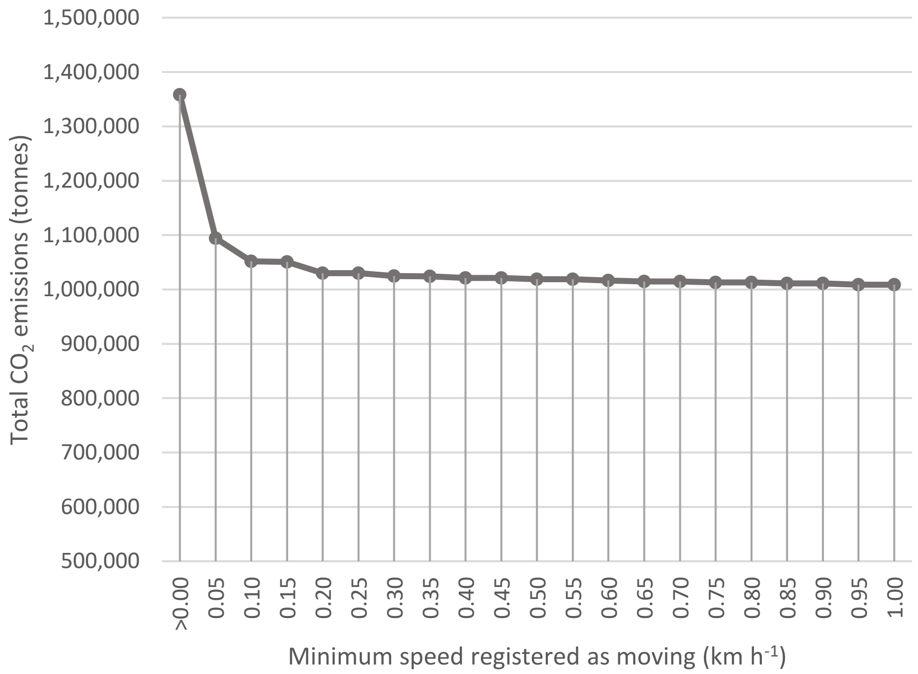

Figure 5.2. Total CO_2 emissions calculated with fixed model parameters other than the minimum speed registered as moving.

The results calculated for the variation through the ranges for each of the other input parameters generally showed either very strong positive or negative correlations (Table 5.4). As would be expected, the results for each of the atmospheric emissions, fuel use and power generated generally followed the same trend. Exceptions to this were see when varying emissions factors, where power generated did not change, therefore no correlation was found between varying emissions factor value and generated power. Varying the instantaneous combined speed range value showed very strong positive correlations for power generated, fuel consumption, fuel based emissions (CO_2, SO_2 and CO) and NO_x. However, a strong negative correlation was observed for both NMVOC and PM. These emissions are highly influenced by engine load, with much greater emission factors when engines are running at low loads. This is almost certainly what causes these trends.

Table 5.4. Pearson's (*r*) linear correlation coefficients for changes in input parameters to response in output results.

Parameter	CO_2	NO_x	SO_2	NMVOC	CO	PM	Fuel	Power
Emission factors	1.000	1.000	1.000	1.000	1.000	1.000	1.000	0.000
Main hotelling /idling load	1.000	1.000	1.000	0.999	1.000	0.999	1.000	1.000
Design speed	-0.974	-0.976	-0.985	-0.929	-0.985	-1.000	-1.000	-0.986
Speed	0.910	0.988	0.910	-0.628	0.910	-0.624	0.910	0.978
Minutes for max. speed	-0.974	-0.976	-0.985	-0.929	-0.985	-1.000	-1.000	-0.986
Engine time during stops	0.996	0.996	0.996	0.996	0.996	0.996	0.996	0.996
Sea margin	-1.000	-1.000	-1.000	-0.944	-1.000	-0.943	-1.000	-1.000
Min. moving speed[a]	-0.789	-0.792	-0.790	-0.785	-0.790	-0.785	-0.790	-0.790

r values can be interpreted as follows: 0 to ±0.1 indicates no correlation, ±0.1 to ±0.3 indicates weak correlation, ±0.3 to ±0.5 indicates medium correlation and ±0.5 or greater indicates strong correlation (Field et al., 2012). All results have $p < 0.01$, suggesting a high level of confidence in the significance of these trends.

a) Calculated for range 0.05 to 1.0 km h^{-1} as the 0.000001 km h^{-1} result is an outlier.

The results of the local perturbation analysis indicate that the parameters that exert the most influence on results when varied are emission factors, main engine hotelling/idling load, design speed and instantaneous speed. Perturbation of other parameters appears to have only a minor influence on results (Table 5.5).

Table 5.5. The results of a local perturbation sensitivity analysis, showing the change in output for a 1% change in input parameters (averaged over a range from -10% to +10% of each input parameter's baseline value.

Parameter	**CO_2**	**NO_x**	**SO_2**	**NMVOC**	**CO**	**PM**	**Fuel**	**Power**
Emission factors	0.837%	0.807%	0.837%	0.941%	0.837%	0.931%	0.837%	0.836%
Main hotelling/ idling load	0.528%	0.568%	0.528%	0.449%	0.528%	0.444%	0.528%	0.545%
Design speed	0.480%	0.620%	0.480%	0.191%	0.480%	0.188%	0.480%	0.527%
Speed	0.324%	0.468%	0.324%	0.179%	0.324%	0.177%	0.324%	0.368%
Minutes for max. speed	0.069%	0.087%	0.069%	0.024%	0.069%	0.024%	0.069%	0.075%
Engine time during stops	0.035%	0.035%	0.035%	0.034%	0.035%	0.035%	0.035%	0.035%
Sea margin	0.023%	0.029%	0.023%	0.017%	0.023%	0.017%	0.023%	0.025%
Min. moving speed[a]	0.013%	0.012%	0.013%	0.013%	0.013%	0.013%	0.013%	0.013%

The results of the global perturbation sensitivity analysis tell a slightly different story (Table 5.6). Emission factors and main engine hotelling/idling load are still the dominant parameters in terms of their influence on model results. Design speed still appears to be important. However, it is the cumulative time used to derive maximum speed (used as a proxy for design speed) that has a more significant influence. The results suggest that the range between lower and upper derived design speeds when using the smoothed combined speed calculation method is very small as it has only a minor effect on results when running through the range of its possible values.

Other parameters have a smaller but not insignificant effect. It is also worth noticing that most parameters have an uneven effect on the results, the majority of which have a stronger negative component.

Table 5.6. The results of a global perturbation sensitivity analysis, showing the change in output with respect to the baseline for the full range of values representing each input parameter.

Parameter		**CO_2**	**NO_x**	**SO_2**	**NMVOC**	**CO**	**PM**	**Fuel**	**Power**
Emission factors	Min	-22.1%	-30.7%	-22.1%	-45.3%	-22.1%	-45.1%	-22.1%	0.0%
	Max	22.1%	30.7%	22.1%	45.3%	22.1%	45.1%	22.1%	0.0%
Main hotelling/ idling load	Min	-26.8%	-27.1%	-26.8%	-27.0%	-26.8%	-26.8%	-26.8%	-27.2%
	Max	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%
Minutes for max. speed	Min	-1.5%	-2.2%	-1.5%	0.0%	-1.5%	0.0%	-1.5%	-1.7%
	Max	8.8%	11.4%	8.8%	2.5%	8.8%	2.5%	8.8%	9.7%
Speed	Min	-4.6%	-10.2%	-4.6%	0.0%	-4.6%	0.0%	-4.6%	-6.2%
	Max	0.7%	0.0%	0.7%	15.1%	0.7%	14.9%	0.7%	0.0%
Sea margin	Min	-4.5%	-6.0%	-4.5%	-0.7%	-4.5%	-0.6%	-4.5%	-5.0%
	Max	1.2%	1.5%	1.2%	0.4%	1.2%	0.4%	1.2%	1.3%
Engine time during stops	Min	-4.4%	-4.3%	-4.4%	-4.3%	-4.4%	-4.3%	-4.4%	-4.3%
	Max	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%
Design speed	Min	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%
	Max	0.9%	1.1%	0.9%	0.4%	0.9%	0.4%	0.9%	0.9%

The results of Monte Carlo sensitivity analysis of the variation in results due to AIS track sampling are shown in Table 5.7. This shows that, when all other parameters are held constant, track sampling generates variability in the results with a standard deviation of all pollutants and power within the range from ±1.56% to ±1.93%. Figure 5.3 shows that these results are approximately evenly distributed around the mean.

Table 5.7. Summary statistics of 250 model runs with different single track samples to represent the activity of each vessel in the fleet.

	CO_2 (kt)	NO_x (kt)	SO_2 (kt)	NMVOC (kt)	CO (kt)	PM (kt)	Fuel Cons. (kt)	Power (GWh)
Mean	1,084.14	17.92	0.68	1.60	2.51	1.11	339.75	1,557.47
St.Dev.	±1.78%	±1.93%	±1.78%	±1.56%	±1.78%	±1.58%	±1.78%	±1.81%
95% c.i.	±3.48%	±3.78%	±3.48%	±3.07%	±3.48%	±3.09%	±3.48%	±3.54%
Min	-7.35%	-8.08%	-7.35%	-5.35%	-7.35%	-5.43%	-7.35%	-7.50%
Max	+4.83%	+5.07%	+4.83%	+3.98%	+4.83%	+3.98%	+4.83%	+4.94%

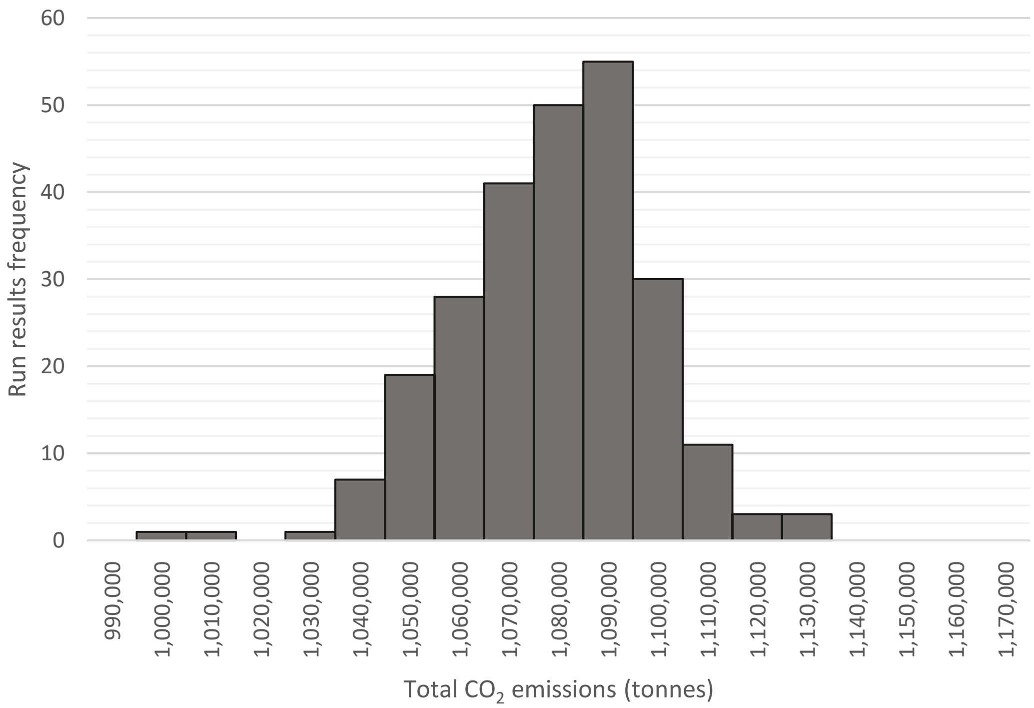

Figure 5.3. Total CO_2 emissions results frequency counts for 250 model runs with different single AIS tracks sampled to represent each modelled vessel's activity. Labels on the horizontal axis represent range lower bounds.

Table 5.8 shows the variation in CO_2 emissions results caused by engine and fuel type sampling. Compared to track sampling, the variation is small, with a standard deviation of just ±756 tonnes (±0.07%). However, the variation in other emissions is more significant, with standard deviations of ±0.86% for NMVOC and ±1.53% for PM. Figure 5.4 shows the results to be slightly skewed from the mean.

Table 5.8. Summary statistics of 250 model runs with different randomly sampled engine and fuel types assigned to each vessel in the fleet for each run.

	CO_2 (kt)	**NO_x (kt)**	**SO_2 (kt)**	**NMVOC (kt)**	**CO (kt)**	**PM (kt)**	**Fuel Cons. (kt)**	**Power (GWh)**
Mean	1,094.36	18.13	0.69	1.61	2.54	1.12	342.95	1,572.92
St.Dev.	±0.07%	±0.32%	±0.06%	±0.86%	±0.06%	±1.53%	±0.06%	±0.00%
95% c.i.	±0.13%	±0.63%	±0.11%	±1.68%	±0.11%	±3.00%	±0.11%	±0.00%
Min	-0.10%	-1.14%	-0.08%	-2.70%	-0.08%	-2.52%	-0.08%	-0.00%
Max	+0.25%	+0.65%	+0.21%	+1.74%	+0.21%	+6.24%	+0.21%	+0.00%

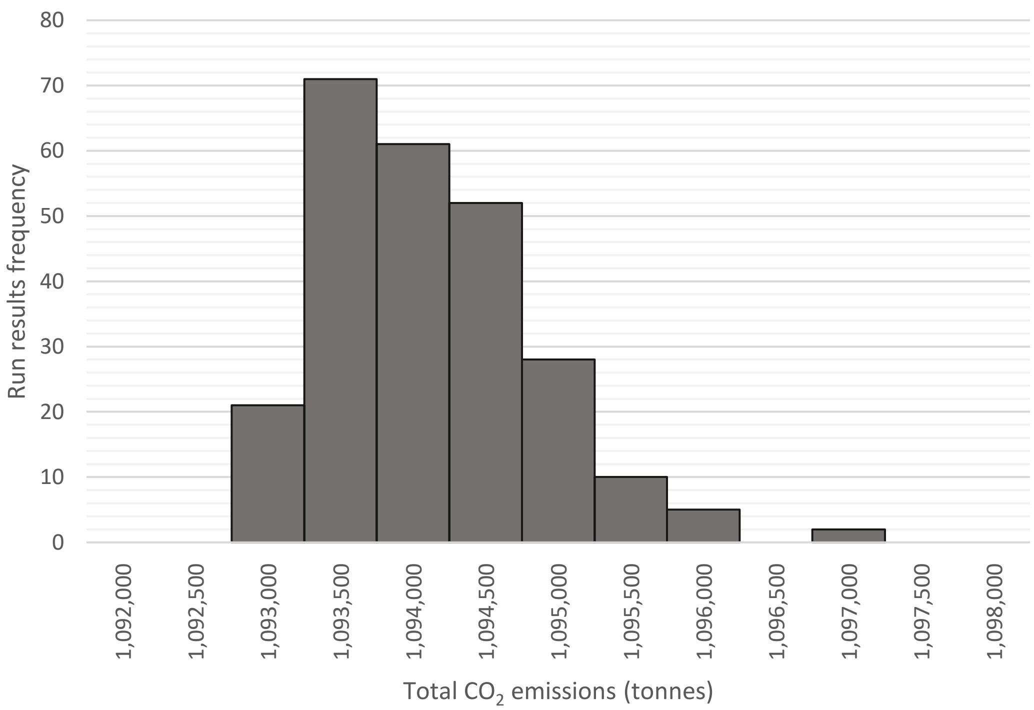

Figure 5.4. Total CO_2 emissions results frequency counts for 250 model runs with different engine and fuel types selected for each vessel and run. Labels on the horizontal axis represent range lower bounds.

Emissions factors, the most significant factor identified in the global perturbation sensitivity analysis, give rise to smaller standard deviation for all pollutants and fuel consumption compared to AIS track sampling. Emission factor uncertainties also cause less variation than engine and fuel type assignment for NMVOC and PM (Table 5.9). Figure 5.5 shows a balanced distribution of results around the mean caused by uncertainty in emission factors.

Table 5.9. Summary statistics of 250 model runs with different randomly sampled emission factors assigned to each vessel in the fleet.

	CO_2 (kt)	**NO_x (kt)**	**SO_2 (kt)**	**NMVOC (kt)**	**CO (kt)**	**PM (kt)**	**Fuel Cons. (kt)**	**Power (GWh)**
Mean	1,094.34	18.13	0.69	1.61	2.54	1.12	342.94	1,572.92
St.Dev.	±0.44%	±0.67%	±0.44%	±0.82%	±0.44%	±0.83%	±0.44%	±0.00%
95% c.i.	±0.85%	±1.32%	±0.85%	±1.61%	±0.85%	±1.62%	±0.85%	±0.00%
Min	-1.28%	-2.02%	-1.28%	-2.37%	-1.28%	-2.40%	-1.28%	-0.00%
Max	+1.14%	+1.74%	+1.14%	+2.15%	+1.14%	+2.16%	+1.14%	+0.00%

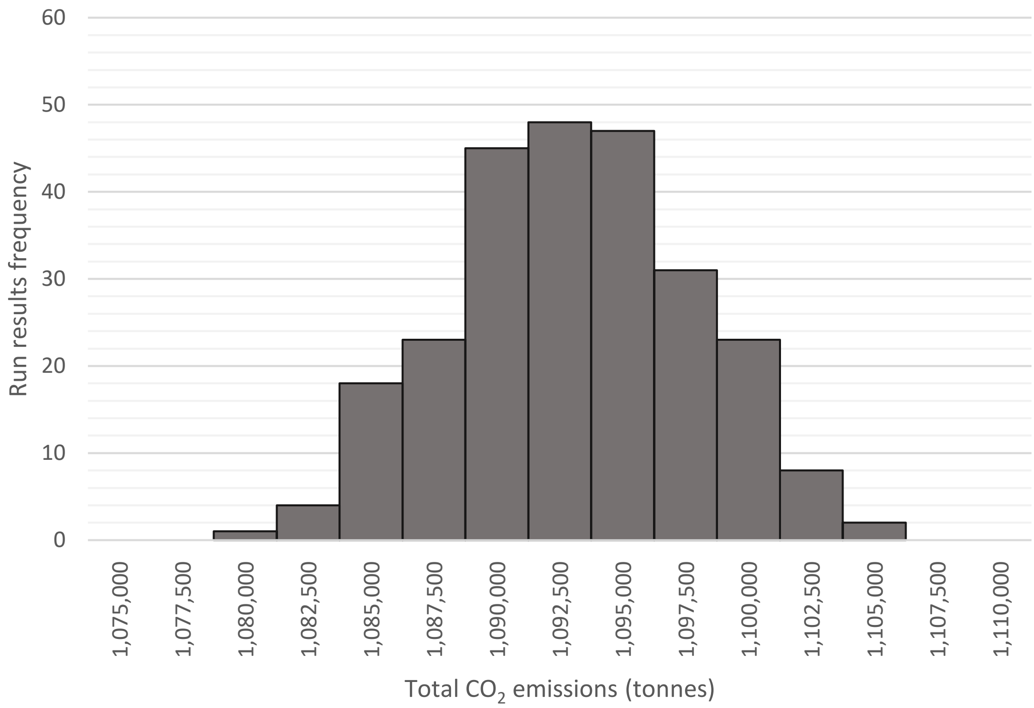

Figure 5.5. Total CO_2 emissions results frequency counts for 250 model runs with different emission factors sampled for each vessel. Labels on the horizontal axis represent range lower bounds.

5.4.2 Uncertainty analysis results

The results of the baseline recalculation with minimum moving speed of 0.1 km h^{-1} are listed in Table 5.10. The results of the Monte Carlo uncertainty analysis are presented in Table 5.11. The results of the uncertainty analysis indicate that emissions of all pollutants are likely to fall within ±6% of the mean (at the 95% confidence interval).

The mean values for the uncertainty analysis are systematically lower than results calculated using the default parameter values for all pollutants, fuel consumption and power generated (Table 5.12). The results calculated using the default input parameter values listed at the end of Section 5.3.2 are between 2.94% and 19.53% above the mean results of the uncertainty analysis. Figures 5.6 to 5.13 show that the results for all pollutants are relatively evenly distributed around the mean and are approximately normally distributed.

Table 5.10. Summary statistics of 250 model runs with different random single track samples to represent the activity of each vessel in the fleet using the higher minimum moving speed of 0.1 km h^{-1}.

	CO_2 (kt)	NO_x (kt)	SO_2 (kt)	NMVOC (kt)	CO (kt)	PM (kt)	Fuel Cons. (kt)	Power (GWh)
Mean	1,038.49	17.20	0.65	1.53	2.41	1.06	325.44	1,492.76
St.Dev.	±2.03%	±2.19%	±2.03%	±1.78%	±2.03%	±1.80%	±2.03%	±2.06%
95% c.i.	±3.98%	±4.29%	±3.98%	±3.49%	±3.98%	±3.52%	±3.98%	±4.03%
Min	-7.98%	-8.74%	-7.98%	-5.91%	-7.98%	-6.00%	-7.98%	-8.13%
Max	+4.83%	+4.96%	+4.83%	+4.40%	+4.83%	+4.41%	+4.83%	+4.86%

Table 5.11. Summary statistics of a 2000 run Monte Carlo simulation uncertainty analysis.

	CO_2 (kt)	NO_x (kt)	SO_2 (kt)	NMVOC (kt)	CO (kt)	PM (kt)	Fuel Cons. (kt)	Power (GWh)
Mean	908.82	14.39	0.57	1.49	2.11	1.03	284.80	1,288.71
St.Dev.	2.54%	2.71%	2.54%	2.61%	2.54%	2.92%	2.54%	2.51%
95% c.i.	4.97%	5.31%	4.97%	5.12%	4.97%	5.71%	4.97%	4.92%
Min	-9.76%	-10.35%	-9.77%	-8.48%	-9.77%	-8.04%	-9.77%	-9.71%
Max	+7.22%	+7.80%	+7.23%	+8.29%	+7.23%	+10.45%	+7.23%	+6.90%

Table 5.12. Differences between the 2000 run Monte Carlo simulation uncertainty analysis and baseline results calculated as the average of 250 runs with independent track samples. Percentages represent the proportion of overestimation in the default parameter values compared to the mean uncertainty analysis results.

	CO_2	**NO_x**	**SO_2**	**NMVOC**	**CO**	**PM**	**Fuel Cons.**	**Power**
Difference (%)	14.27%	19.53%	14.27%	2.90%	14.27%	2.94%	14.27%	15.83%

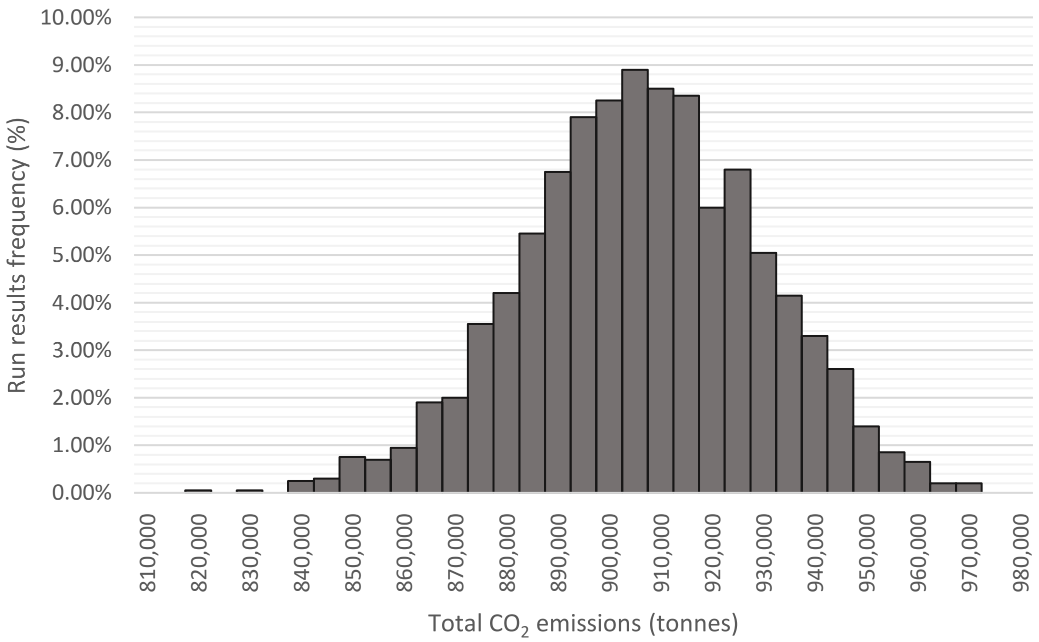

Figure 5.6. Total CO_2 emissions results frequencies for uncertainty analysis comprising 2000 Monte Carlo simulation runs. Labels on the horizontal axis represent range lower bounds.

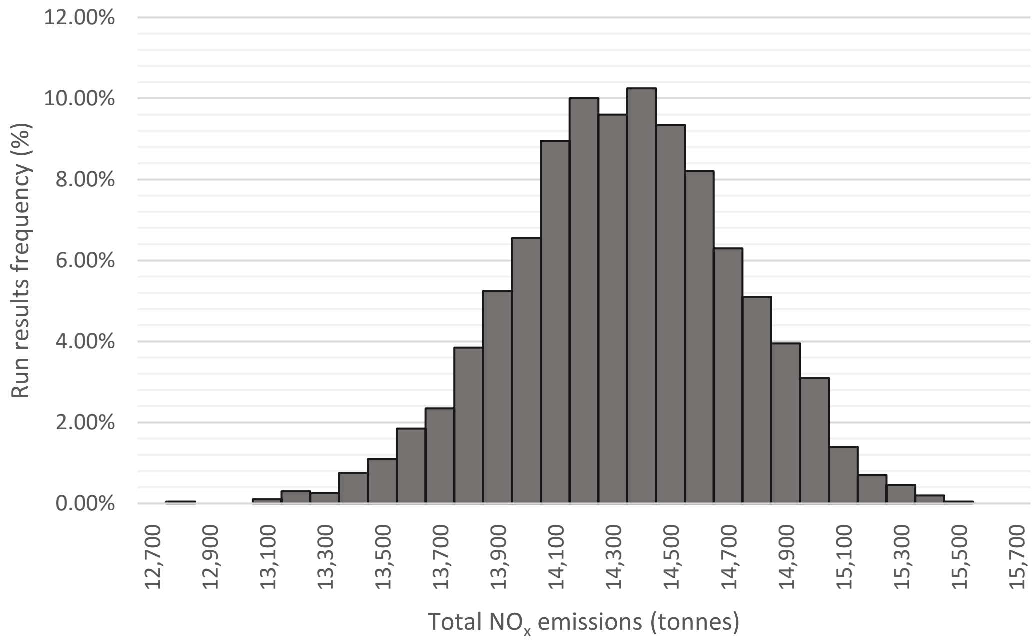

Figure 5.7. Total NO_x emissions results frequencies for uncertainty analysis comprising 2000 Monte Carlo simulation runs. Labels on the horizontal axis represent range lower bounds.

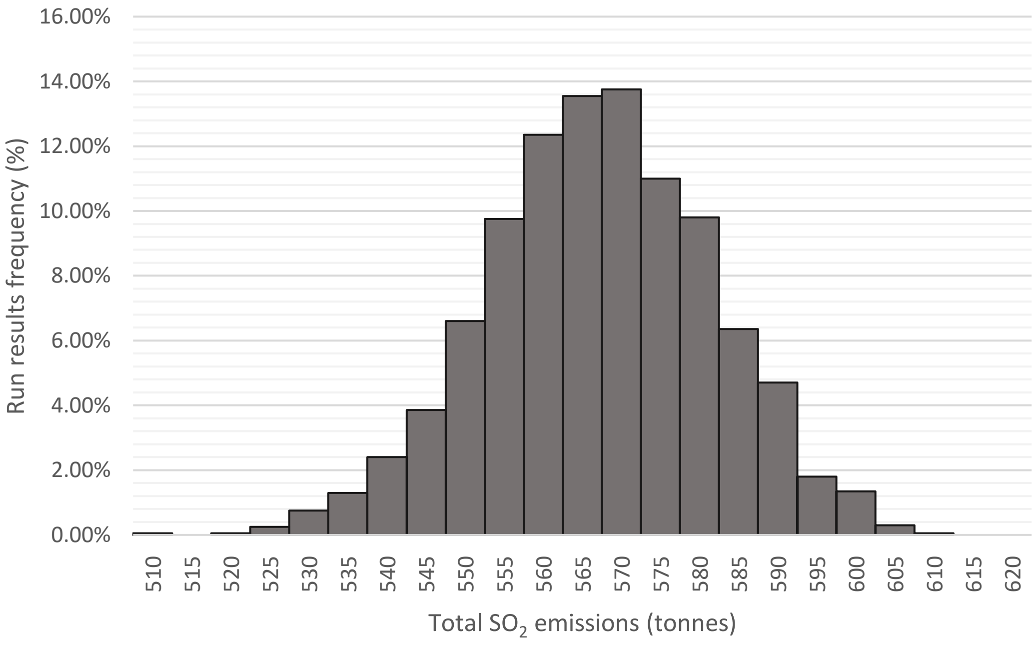

Figure 5.8. Total SO_2 emissions results frequencies for uncertainty analysis comprising 2000 Monte Carlo simulation runs. Labels on the horizontal axis represent range lower bounds.

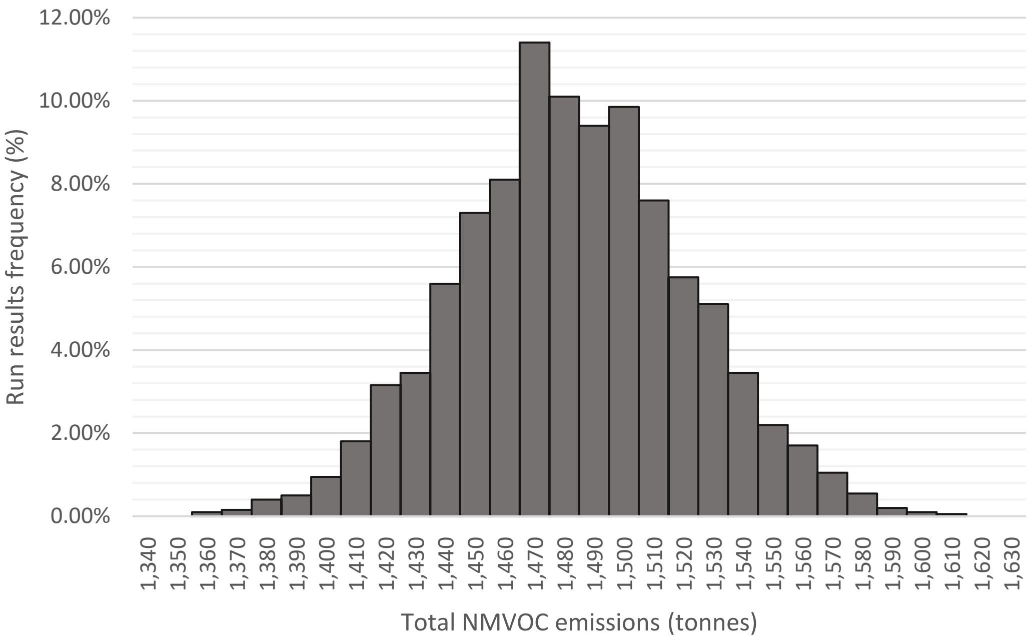

Figure 5.9. Total NMVOC emissions results frequencies for uncertainty analysis comprising 2000 Monte Carlo simulation runs. Labels on the horizontal axis represent range lower bounds.

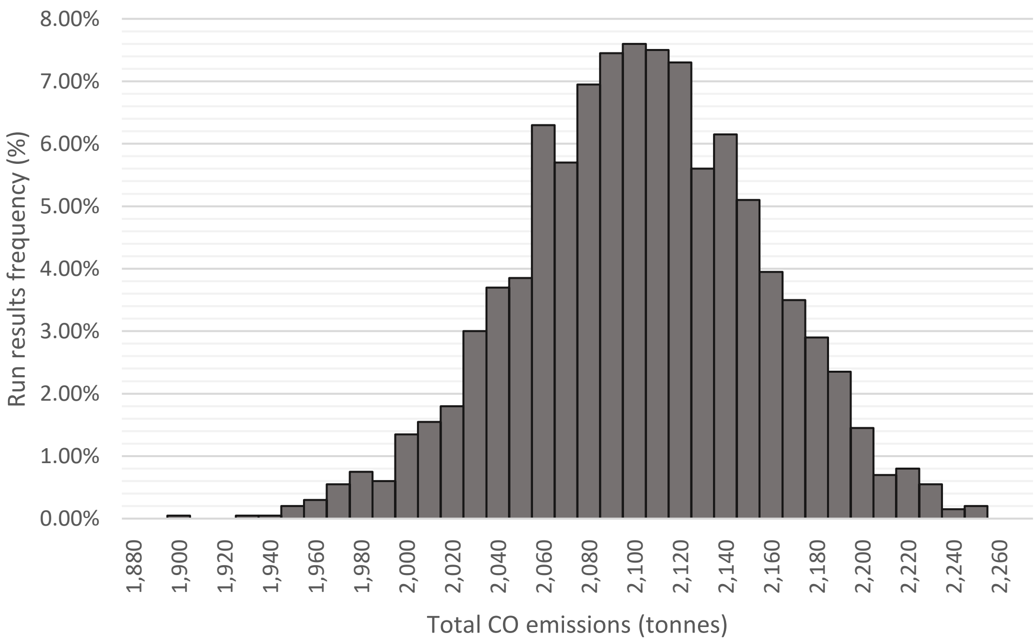

Figure 5.10. Total CO emissions results frequencies for uncertainty analysis comprising 2000 Monte Carlo simulation runs. Labels on the horizontal axis represent emissions range lower bounds.

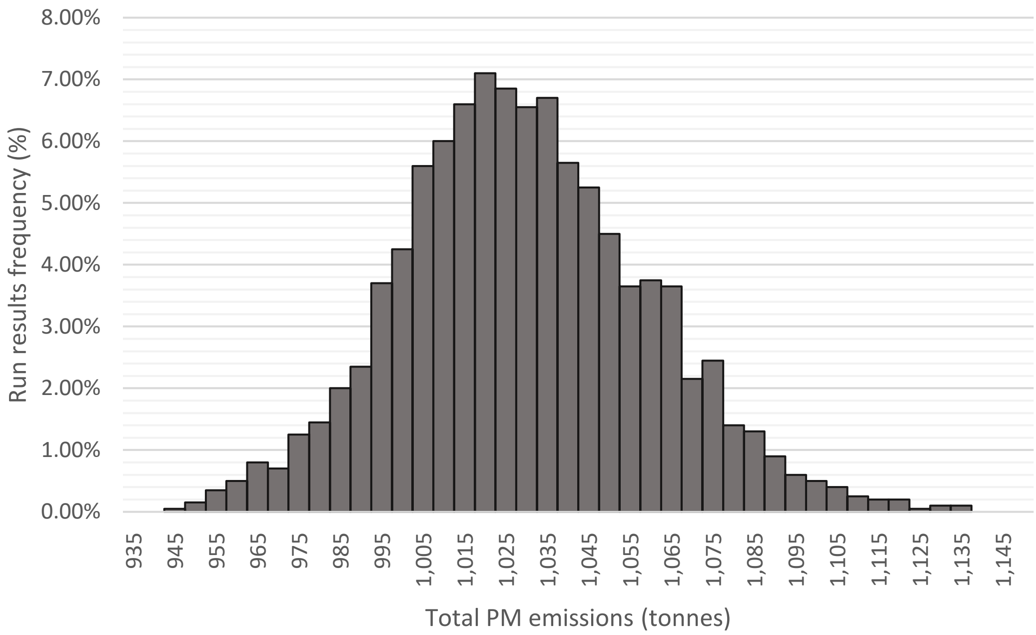

Figure 5.11. Total PM emissions results frequencies for uncertainty analysis comprising 2000 Monte Carlo simulation runs. Labels on the horizontal axis represent range lower bounds.

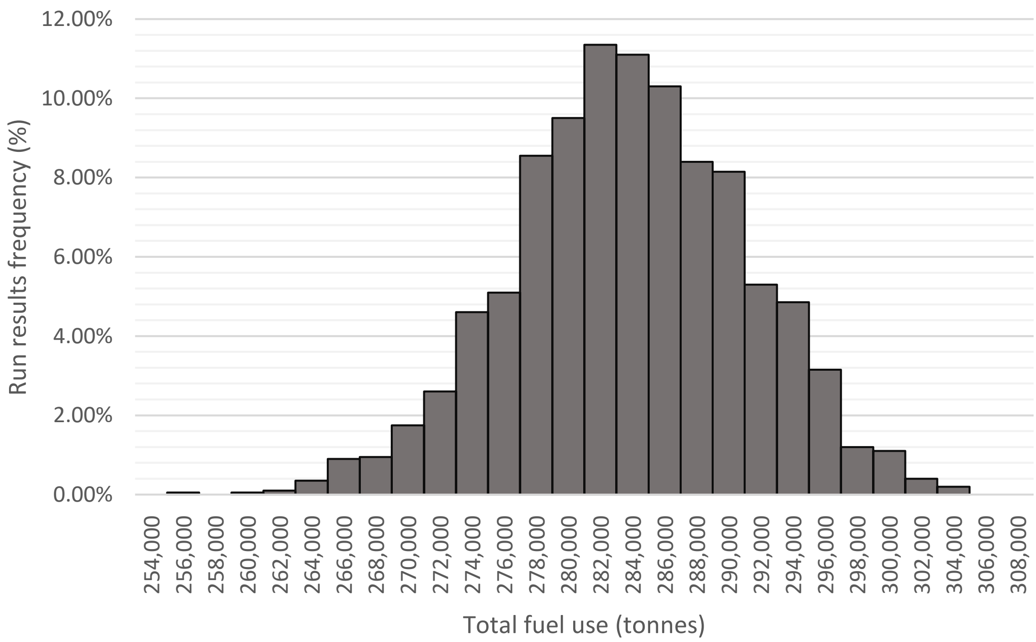

Figure 5.12. Total fuel consumption results frequencies for uncertainty analysis comprising 2000 Monte Carlo simulation runs. Labels on the horizontal axis represent range lower bounds.

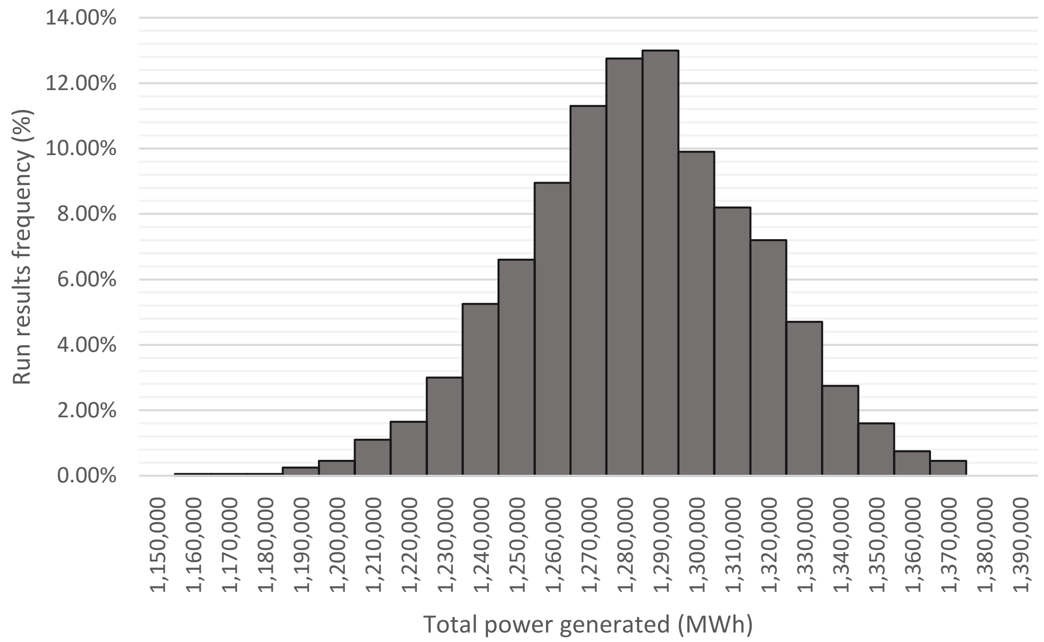

Figure 5.13. Total power generation results frequencies for uncertainty analysis comprising 2000 Monte Carlo simulation runs. Labels on the horizontal axis represent range lower bounds.

5.5 Discussion

The results from the various speed calculation methods trialled differ significantly. Emissions calculated using only speeds from AIS data are significantly higher than those calculated using the alternative speed calculation methods. This is, in part, due to lower estimates of design speed deduced from AIS data and therefore higher average relative speeds and engine loads. These differences highlight that selecting the speed calculation methodology is a major decision when using AIS data to produce emissions inventories, especially when AIS data is the best source of information available for estimating vessel design speed.

Using both the distance and duration derived from AIS data and the speeds recorded directly in the AIS data themselves in a combined method for speed calculation (see Section 3.3.5) seems a good way to utilise more information than either of the methods commonly used in the literature. It also offers a range of speed values that can be used to contribute to the quantification of uncertainty in emissions inventories.

The results of the sensitivity analysis showed that the results were sensitivity to variation in all of the input parameters included in the analysis. The results are most sensitive to uncertainties in AIS track sampling, followed by emission factors, engine and fuel type sampling and the parameterization of the engine load calculation formula. The use of engine load override rules accounts for a relatively minor but still not insignificant increase in the emissions calculated. An increase is expected given that the engine load override rules used override the engine load calculated from relative speed with a comparatively high engine load. This suggests that the methodology detects vessels exhibiting trawling and dredging behaviours for a relatively small proportion of overall moving time.

The sampling of AIS tracks is an inherent source of uncertainty when vessels cannot be directly matched to AIS records. This analysis suggests that it will be one of the most significant sources of uncertainty when calculating emissions for small commercial watercraft unless vessel databases are developed that include MMSI number identifiers for these fleets and the uptake of AIS technology approaches 100%. However, the results of this research indicate that fleet level results are relatively stable despite the use of sampled AIS tracks as the source of vessel activity data when modelling relatively large fleets.

Due to the inherent stability that modelling large fleets provides to results, what is more significant are the sources of potential systemic uncertainty, i.e. the sources of uncertainty that have a biased effect. For example, the default value for main engine hotelling/idling load was set at 20% prior to the undertaking of uncertainty and sensitivity analysis and then replaced with a range value from 10% to 20%. The original value had been taken from a standard guidebook for modelling emissions from waterborne navigation (Trozzi et al., 2016). The results presented in Table 5.6 indicate that this kind of systematic alteration of input parameters has a significant effect on the mean results calculated. Therefore, identifying realistic and unbiased values for these input parameters is important for the accuracy of results. The parameters that appear to have generated the most significant bias are the parameters affecting engine load calculation. Namely, main engine hotelling/idling load, sea margin and design speed.

The results of the local sensitivity analysis indicated that perturbation of design speed could have a significant effect on model outputs. Given that design speed was derived from AIS track data in the case study example, it was a significant source of uncertainty for which bias is difficult to quantify. It is differences in track derived design speed that accounts for most of the variation in results between the different speed calculation methods trialled.

This implies that collecting data on vessel design speeds would reduce uncertainty significantly.

The full uncertainty analysis was run with a slightly higher value for minimum moving speed of 0.1 km h^{-1} compared to 0.05 km h^{-1}. This higher speed was selected as it appears to be the point at which the rate of change in emissions slowed when cycling through the range of minimum speeds tested (Figure 5.2). This was taken as an indication that selecting a minimum moving speed around this value reduces the potential for emissions overcalculation due to GPS 'noise' or vessels drifting whilst moored or at anchor. Using the higher minimum moving speed was shown to reduce emissions by 3.9% when using default values for all other model parameters (Figure 5.3).

For comparison, a mean value was calculated based 250 runs with different random track samples. The difference in results between this and the uncertainty analysis can be viewed as the net effect of the biases introduced by selecting single parameter values that were not central to the ranges used for the uncertainty analysis. Considering total CO_2 emissions, the mean results of track sampling sensitivity analysis carried out with the higher minimum moving speed were 1,038.5 kt, compared to 907.8 kt for the full uncertainty analysis, a difference of 14.3%. The mean fuel consumption calculated from the 2000 Monte Carlo simulation runs was 284.8 kt ±5% (with a 95% confidence interval). The range of fuel use at the 95% confidence interval is from 270.6 kt to 299.0 kt.

5.6 Conclusion

The findings of the work presented in this chapter highlight that there are many sources of uncertainty that affect results. There are some structural decisions that require careful consideration, such as the speed calculation methodology and the use of engine load override rules. These are both considerations that seem to be afforded little attention in the literature.

Despite the apparent significance of track sampling and emissions factor ranges in generating uncertainty in the results, it is suggested that the areas where additional data and research effort is most important to reduce uncertainty are the parameters that can introduce the most significant bias in results. From the findings in this chapter, the factors affecting engine load calculation are found to be the largest contributors to potential bias. There is a paucity of information in the literature for both main engine hotelling/idling load and sea margin, both of which have a significant effect on engine load calculation. There is also limited information available on the design speeds of the fishing vessels used in this case study. The results of this analysis indicate that errors and bias in these input parameters can lead to significant systematic bias in results.

The results of the uncertainty analysis seem to indicate that the default input parameter values proposed early in the chapter are likely to result in an overestimation of emissions. By selecting values closer to the middle of the ranges used to represent input parameters, better quality results can be expected. This is shown to be the case in Chapter 6, where results are compared to those produced using an alternative methodology and comparable findings in the literature. Overall, the uncertainty in results appears to have a range of around ±5% for fuel use and all pollutant emissions at the 95% confidence interval, indicating good stability of results.

6 Case study emissions inventory for the UK fishing fleet: comparison of an AIS-based and a fuel-based methodology

The purpose of this chapter is to present the results of using the bottom-up activity-based methodology using AIS data outlined in Chapters 3 and 4 to calculate an inventory of fuel use and atmospheric pollution emissions for the UK fishing fleet over the duration of a year from May 2012 to May 2013. The findings presented in Chapter 5 are used to calibrate model input parameters. An inventory is calculated using an alternative fuel-based methodology, which is used for comparison and validation of the activity-based methodology. Results are also compared to published inventories where possible. This chapter satisfies objective 4 of this project:

> *"To calculate an emissions inventory for a case study fleet of small commercial vessels and assess the validity of results.."*

6.1 Introduction

Throughout the 20th century fisheries became highly dependent on fossil fuels (Tyedmers et al., 2005), and are a major source of greenhouse gas emissions and other atmospheric pollutants (Driscoll & Tyedmers, 2010). In 2012, the United Kingdom (UK) fishing fleet was made up of 6434 vessels, comprising a significant fraction of the UK shipping fleet (EC, 2013a).

Previous emissions inventories for the fishing industry have been compiled based on fuel use data surveyed from vessel operators (Hospido & Tyedmers, 2005; Iribarren et al., 2010; Tyedmers, 2001; Vázquez-Rowe et al., 2010; Ziegler & Hansson, 2003). Larger fishing vessels have also been included in global shipping emissions inventories using activity-based methods (Buhaug et al., 2009; Corbett & Köhler, 2003; Endresen et al., 2003; Eyring et al., 2005; Jalkanen et al., 2014; Smith et al., 2014). Activity-based methodologies have been widely accepted as more accurate than fuel-based methods for calculating shipping emissions inventories (Buhaug et al., 2009; Smith et al., 2014). However, complete emissions inventories of fishing fleets continue to rely on fuel-based methods. One possible reason for this is a the lack of complete activity data records. For example, AIS devices are not mandatory for the majority of fishing vessels and, therefore, only a fraction of the fleet has them installed (Coello et al., 2015). Another issue is the requirement to detect and model fuel consumption of vessels engaged in trawling and dredging activities.

This chapter presents a emissions inventory of the UK fishing fleet calculated using the activity-based methodology based on AIS data described in Chapters 3 and 4. Significantly, the methodology uses an activity-sampling approach that is necessary for fleets for which not all vessels have AIS technology fitted, such as the UK fishing fleet. It also introduces a new way to identify when vessels are engaged in trawling or dredging and adjusts the engine load used in emissions calculation accordingly. As a means of comparison and corroboration, an emissions inventory is also calculated from fuel consumption rates per unit of catch and total catch landed by the UK fishing fleet.

6.1.1 Previous emissions inventorying methods

Methods for the quantification of emissions from the fishing industry have generally relied on the use of primary or secondary data on fuel use reported by fishing vessel operators that are used to determine fuel consumption per unit of catch landed. These data are scaled-up using either fleet vessel numbers or records of total landings to produce emissions inventories for regional, national or international fleets (Hospido & Tyedmers, 2005; Iribarren et al., 2010; Tyedmers, 2001; Tyedmers et al., 2005; Vázquez-Rowe et al., 2010; Whall et al., 2002; Ziegler & Hansson, 2003).

Such methods are useful for quantifying and comparing the carbon intensity of various seafood products and fishing methods (Tyedmers, 2001; Thrane, 2004a, 2004b; Ziegler & Hansson, 2003; Ziegler & Valentinsson, 2008); as well as changes in carbon and fuel intensity over time due to changes in fish stocks and fishing methods (Schau et al., 2009). However, they are less useful for producing the kind of spatially and temporally resolved emissions inventories typically used as inputs to atmospheric chemical transport and dispersion models.

Fishing vessels of 100 GT and above have also been included in various activity-based emissions inventories. The activity data used has ranged from educated assumptions (Corbett & Köhler, 2003; Endresen et al., 2003; Eyring et al., 2005), port arrivals and departures (Dalsøren et al., 2009), AIS data used to estimate days at sea and engine loads (Buhaug et al., 2009) or AIS data used to produce fully vessel-specific bottom-up inventories (Jalkanen et al., 2014; Smith et al., 2014). However, the omission of fishing vessels under

100 GT is likely to result in considerable underestimation of emissions from the sector (Endresen et al., 2007). Reliable inclusion of fishing vessels in activity-based estimates based on empirical data, such as AIS data also requires modelling of the elevated engine loads of vessels engaged in trawling and dredging operations to avoid potential underestimates of emissions. This is an issue that previous activity-based methodologies have not addressed.

6.2 Materials and methods

6.2.1 Fuel-based method

The *Scientific Fishery Data* portal, run by the European Commission (EC), provides data on total landings by country, fishing vessel size and gear type for 2008, 2009 and 2010 (EC, 2013b). This was used to obtain information on total landings by vessels of different gear types for the UK (Table 6.1). It also provides fuel efficiency data for various European Union (EU) countries for each fishing vessel category (Tables B.1 to B.13, Appendix B). The fuel efficiency data give a rate of fuel use per unit of catch, expressed in litres per kilogram (L/kg), produced from data that vessel operators provide to the EC.

Table 6.1. Total landings by UK fishing vessel category (EC, 2013b).

Vessel category	**UK Landings 2008 (kg)**	**UK Landings 2009 (kg)**	**UK Landings 2010 (kg)**
Beam trawlers (< 12 m)	515,564	650,206	315,638
Beam trawlers (12-24 m)	3,267,066	3,744,021	4,249,213
Beam trawlers (24-40 m)	8,291,496	6,316,458	7,819,519
Beam trawlers (≥ 40 m)	5,867,651	6,684,815	7,843,600
Demersal trawlers and/or demersal seiners (< 12 m)	9,949,386	9,660,181	9,871,153
Demersal trawlers and/or demersal seiners (12-24 m)	75,604,466	77,627,917	72,400,926
Demersal trawlers and/or demersal seiners (24-40 m)	58,760,550	63,493,796	62,841,105
Demersal trawlers and/or demersal seiners (≥ 40 m)	24,472,585	21,876,081	26,656,554

Vessel category	UK Landings 2008 (kg)	UK Landings 2009 (kg)	UK Landings 2010 (kg)
Dredgers (< 12 m)	5,475,504	3,983,135	4,352,353
Dredgers (12-24 m)	18,452,518	19,528,757	24,030,115
Dredgers (24-40 m)	77,600,95	12,420,909	0
Dredgers (≥ 40 m)	4,424,000	0	3,380,000
Drift and/or fixed netters (< 12 m)	6,370,474	6,436,064	6,653,501
Drift and/or fixed netters (12-24 m)	1,925,281	1,894,493	1,869,835
Drift and/or fixed netters (24-40 m)	2,387,361	2,662,653	2,729,474
Pelagic trawlers (12-24 m)	0	0	56864
Pelagic trawlers (≥ 40 m)	12,144,936	0	0
Purse seiners (< 12 m)	10,169	192,287	145,922
Purse seiners (12-24 m)	3,320,722	2,968,464	4,070,743
Purse seiners (24-40 m)	0	0	0
Purse seiners (≥ 40 m)	271,459,977	282,458,782	291,697,519
Vessels using active and passive gears (< 12 m)	11,607	7,917	49,617
Vessels using active and passive gears (12-24 m)	16,509	0	0
Vessels using hooks (< 12 m)	1,728,370	2,152,001	2,619,282
Vessels using hooks (12-24 m)	163,551	261,436	282,183
Vessels using hooks (24-40 m)	5,300,293	5,986,799	5,482,226
Vessels using hooks (≥ 40 m)	1,028,037	812,016	236,725
Vessels using polyvalent active gears only (< 12 m)	346,324	763,226	199,009
Vessels using polyvalent active gears only (12-24 m)	112,844	674,401	1,575,443
Vessels using polyvalent passive gears only (< 12 m)	464,099	371,356	585,400
Vessels using pots and/or traps (< 12 m)	29,412,180	26,952,669	28,500,338
Vessels using pots and/or traps (12-24 m)	14,417,569	14,492,785	15,460,285
Vessels using pots and/or traps (24-40 m)	1,531,637	1,564,094	1,582,940

Fuel efficiency data were not available for all vessel categories for each year and country. Notably, UK fuel efficiency data were only available for 2008 and 2009. Where UK data were available, the data for both years were averaged to give the fuel efficiency figures used in this research. When UK data were unavailable for a vessel category, data from other countries were used based on a ranking of similarity to UK data using the mean difference between the UK and other countries' fuel efficiencies (Table B.14, Appendix B).

Mean differences were calculated for active gear types (e.g. trawling and dredging), passive gear types (e.g. nets and hooks) and all gear types (Table B.14, Appendix B) based on the vessel categories with data for the UK and other countries that could be compared (Tables B.1, B.2, B.4, B.9 and B.13 of Appendix B). For vessel categories where data were unavailable for the UK, fuel efficiencies from the closest matching country to the UK were taken. The fuel efficiency used was the mean of all years available for the selected country and vessel category (Table 6.2).

For example, Table 6.1 shows landings by UK pelagic trawlers (≥ 40 m). However, no fuel efficiency figures are available for UK pelagic trawlers (Table B.5, Appendix B). Pelagic trawlers are categorised as vessels that use active gear. Using Tables B.5 and B.14 in Appendix B, fuel efficiency figures can be selected for the country that has the most similar active gear fuel efficiency rates to the UK, which is Lithuania. Taking the mean of the fuel efficiency figures for Lithuania (0.43 L/kg in 2009 and 0.66 L/kg in 2010) gives a fuel efficiency of 0.55 L/kg.

In some vessel categories data were only available for one country, in which case those fuel efficiency figures were used. For example, Table 6.1 contains landings by beam trawlers < 12 m, a category of vessel for which only Germany has registered fuel efficiency figures (Table B.1, Appendix B). Certain vessel categories had no data at all. In these cases, the fuel efficiency from the most similar category of vessel was used as a proxy. For example, a fuel efficiency rate was required for dredgers > 40 m but no fuel efficiency data were available for this type of vessel. Therefore, the fuel efficiency data for dredgers 24 – 40 m from the UK were used as a proxy.

The total landings data (Table 6.1) were multiplied by the fuel efficiency figures used (Table 6.2) to estimate fuel consumption by the UK fishing fleet (Table 6.3). To convert fuel use from litres to tonnes, it was assumed that all vessels used Marine Diesel Oil, with a density of 1,191 litres per tonne (Defra/DECC, 2012). Tier 1 emissions factors were taken from the

EMEP/EEA air pollutant emission inventory guidebook 2016 (Trozzi et al., 2016) to calculate emissions.

Table 6.2. Fuel efficiency figures compiled from European Scientific Fishery Data (based on EC, 2013b). Fuel efficiency is expressed in litres of fuel (L) used per kilogram (kg) of catch landed.

Vessel category	**Fuel efficiency used (L/kg)**	**Data used**	**Reason**
Beam trawlers (< 12 m)	0.68	Germany	Only country available
Beam trawlers (12-24 m)	1.93	UK	
Beam trawlers (24-40 m)	1.49	UK	
Beam trawlers (≥ 40 m)	2.75	Netherlands	Only country available
Demersal trawlers and/or demersal seiners (< 12 m)	0.94	UK	
Demersal trawlers and/or demersal seiners (12-24 m)	1.00	UK	
Demersal trawlers and/or demersal seiners (24-40 m)	0.92	UK	
Demersal trawlers and/or demersal seiners (≥ 40 m)	0.71	UK	
Dredgers (< 12 m)	0.61	UK	
Dredgers (12-24 m)	0.47	UK	
Dredgers (24-40 m)	0.65	UK	
Dredgers (≥ 40 m)	0.65	UK Dredgers (24-40 m)	No data available so used as proxy
Drift and/or fixed netters (< 12 m)	0.56	UK	
Drift and/or fixed netters (12-24 m)	0.58	UK	
Drift and/or fixed netters (24-40 m)	0.41	UK	
Pelagic trawlers (12-24 m)	0.42	Italy	Active gear closest match

Vessel category	Fuel efficiency used (L/kg)	Data used	Reason
Pelagic trawlers (≥ 40 m)	0.55	Lithuania	Active gear closest match
Purse seiners (< 12 m)	0.16	Portugal	Only country available
Purse seiners (12-24 m)	0.12	Portugal	Passive gear closest match
Purse seiners (24-40 m)	0.13	Portugal	Passive gear closest match
Purse seiners (≥ 40 m)	0.13	Portugal Purse Seiners (24-40 m)	No data so used as proxy
Vessels using active and passive gears (< 12 m)	0.29	France	All gear closest matches
Vessels using active and passive gears (12-24 m)	0.58	Denmark	All gear closest matches
Vessels using hooks (< 12 m)	0.68	UK	
Vessels using hooks (12-24 m)	0.78	Portugal	Passive gear closest match
Vessels using hooks (24-40 m)	0.86	UK	
Vessels using hooks (≥ 40 m)	0.86	UK Vessels using hooks (24-40 m)	No data so used as proxy
Vessels using polyvalent active gears only (< 12 m)	0.93	France	Only country available
Vessels using polyvalent active gears only (12-24 m)	1.03	France	Only country available
Vessels using polyvalent passive gears only (< 12 m)	0.03	Latvia	Passive gear closest match
Vessels using pots and/or traps (< 12 m)	0.71	UK	

Vessel category	Fuel efficiency used (L/kg)	Data used	Reason
Vessels using pots and/or traps (12-24 m)	0.73	UK	
Vessels using pots and/or traps (24-40 m)	0.73	UK Vessels using pots and/or traps (12-24 m)	No data so used as proxy

6.2.2 Bottom-up activity-based method

Emissions from the fishing industry were calculated using a bottom-up activity-based methodology and software model based on AIS data. Chapter 3 provides a detailed description of the methodology and software used to calculate emissions. AIS data for fishing vessels within the area between latitudes 40˚N and 65˚N and longitudes 20˚W and 12˚E between 9th May 2012 and 15th May 2013 were provided by *MarineTraffic.com* (MarineTraffic.com, 2013). The data provided comprised an archive of over 55.5 million individual AIS messages associated with 5188 unique Marine Mobile Service Identity (MMSI) numbers, each of which represents a vessel broadcasting AIS data. Further analysis of the data showed that 653 of these tracks were of sufficiently high quality and were classified as belonging to the UK fleet of vessels using the filtering criteria recommended in Chapter 4. This was taken as the sample of activity data for the UK fleet.

The European Commission (EC) maintains the Community Fleet Register database of fishing vessels that operate under the flags of EC member states (EC, 2013a). This was used to obtain a list of vessels licenced in the UK at the start of each month from May 2012 to May 2013. These data were then combined into a single list of all vessels active throughout the study period with appropriate start and finish dates so that vessels registered or deregistered throughout the study could be treated appropriately. The aggregated list used in the study contained characteristics of 6434 vessels. The full vessel characteristics database is available in the accompanying electronic material.

In addition to these key datasets, a database containing the location of 588 ports in the study area was compiled. These ports were initially identified using online mapping services and omissions were identified by projecting the locations where vessels stopped (as shown by the AIS data used in the study) onto aerial photographs of the study area using publicly available satellite and aerial imagery tools. This helped to identify additional smaller ports and harbours not listed on maps. The full list of ports identified is available in CaseStudyData directory of the accompanying electronic material.

Unfortunately, the ECCFFR fishing fleet database did not contain MMSI numbers and therefore it was not possible to reliably match vessel data to AIS tracks. For this reason, a sampling approach was taken, using multiple tracks as a sample of activity for each vessel during emissions calculation. The *MarineTraffic.com* website was used as a source of supplementary data, which are accessed using vessels' MMSI numbers (MarineTraffic.com, 2013). The ECCFFR database also lacks information on vessel design speeds and so these were estimated from the data with the assumption that the maximum speed recorded for at least 20 minutes for any AIS activity track was a reasonable proxy for a vessel's design speed.

The modelling approach used required the creation of *vessel type profiles*, which contain the settings used in emissions calculation for vessels of that type. The vessel database structure, being non-specific to fishing vessels, does not specifically enable the storage of the fishing gear type used. Therefore, *vessel type profiles* were created to allow differentiations between vessels using different gear types. A total of 44 *vessel type profiles* were created, including 10 polyvalent categories for vessels using more than one type of gear. For trawlers and dredgers, the gear types were further subdivided into different engine power classes so that they could be related to appropriate *engine load override rules* (Table 3.4).

Fishing vessels such as trawlers and dredgers tow fishing gear, which results in high engine loads at relatively low speeds (Suuronen et al, 2012). An exchange of email correspondence with staff at Seafish, the industry body representing the UK seafood industry, enabled the generation of *engine load override rules* for use with trawling and dredging fishing vessels (Table 3.4) (Montgomerie, 2013). These rules were associated with the appropriate *vessel type profiles* and AIS activity data fitting these *engine load override rules* were identified whilst processing AIS data.

A database of emission factors was created based on the *EMEP/EEA air pollutant emission inventory guidebook 2016* Tier 3 emissions factors (Trozzi et al., 2016). In order to select the correct emission factors, engine and fuel type are required. However, the ECCFFR database did not contain these data and, therefore, fleet level averages were used instead. These were also available for fishing vessels in Trozzi et al. (2016) (Table 3.3). For each vessel in the fleet, each engine type was associated with a probability equal to the percentage value in Table 3.3. Emissions were calculated for each engine type, multiplied by the probability and summed to give a total estimate of emissions for each vessel.

It is not mandatory for fishing vessels to use AIS technology. Therefore, an activity sampling methodology was used to allow calculation of emissions for all vessels based on matching each individual vessel in the ECCFFR database to 30 AIS tracks from similar types of vessels. A sample size of 30 AIS tracks was selected for each vessel based on the rationale outlined in Chapter 4.

Based on the sensitivity analysis described in Chapter 5 and the results of the fuel-based method used as a basis for comparison in this chapter, the following calibrated run settings values were used:

- Combined speed calculation method (see Section 3.3.5)
- minimum moving speed of 0.1 km h^{-1},
- 20-minute minimum cumulative time for derived maximum speeds,
- main engine idling/hotelling load of 15%,
- sea margin of 20%,
- main engine running time during stops of 5% of stop duration and between 15 and 30 minutes,
- auxiliary engine running time during stops of 25% of stop duration and between 60 and 720 minutes,
- engine load override rules as detailed in Table 3.4.

The track sampling pool was filtered in the way described in Chapter 4 to include only AIS tracks with:

- no more than 10% of track segments containing errors,
- minimum ½ year duration,
- a minimum of 1,000 AIS data points,
- at least 10% of port stops at UK ports

In terms of error handling, time intervals between two consecutive AIS points of over 60 minutes in duration were considered too long to reliably calculate the speed of the vessel for the journey between them. Track segments with an average speed of over 100 km h^{-1} were also identified as erroneous. In these cases, an appropriate average speed was assigned depending on whether the vessel was operating within a port area or not. A map of total annual CO_2 emissions was also created with errors excluded.

The source code for the software developed to implement the methodology described in Chapter 3 and 4 and used to produce the results in this chapter is provided in the accompanying material. The case study datasets are also provided so that the model can be run if desired.

6.3 Results

The fuel consumption calculated using the fuel-based method is presented by vessel category and year in Table 6.3. Total fuel consumption and emissions calculated from the quantity of fuel consumed are presented in Table 6.4. The results calculated using a bottom-up AIS activity-based approach are presented in Tables 6.4 and 6.5. Taking the average quantity of fuel consumed as the basis for comparison: the average annual fuel consumption for years 2008-2010, calculated using the fuel-based methodology, was 251.8 kt. Fuel use in both main and auxiliary engines, calculated using the bottom-up AIS activity-based approach developed, was 270.8 kt. Of this, 19% of fuel was calculated as being used in auxiliary engines (Table 6.5).

Looking at fuel use and emissions aggregated by major vessel type and GT; vessels under 100 GT consume 43.5% of all fuel used by the fishing fleet (Table 6.6). Trawlers, i.e. vessels using trawling gear as either their main or secondary fishing gear, consume 93.2% of the total fuel used by the fleet (Table 6.6). This is higher than the proportion suggested by the results of the alternative methodology, which suggest around 66% of emissions are attributed to trawlers (Table 6.3).

Figure 3.11 shows the geographical distribution of CO_2 emissions. As expected, the distributions of emissions of other pollutants are also very similar. Areas of high emissions intensity are generally clustered around ports.

Table 6.3. Fuel use by vessel category 2008-2010 calculated from European Commission fisheries statistics (kilotonnes).

Vessel category	**Fuel use 2008**	**Fuel use 2009**	**Fuel use 2010**
Beam trawlers	29.51	29.78	34.96
Demersal trawlers and/or demersal seiners	131.31	134.89	133.01
Dredgers	16.74	16.53	13.56
Drift and/or fixed netters	4.75	4.87	4.98
Pelagic trawlers	5.61	0.00	0.02
Purse seiners	29.97	31.16	32.27
Vessels using active and passive gears	0.01	0.00	0.01
Vessels using hooks	5.66	6.31	5.81
Vessels using polyvalent active gears	0.37	1.18	1.52
Vessels using polyvalent passive gears	0.01	0.01	0.01
Vessels using pots and/or traps	27.31	25.91	27.44
Total	251.25	250.62	253.59

Table 6.4. Fuel use and emissions from UK fishing activities 2008-2010 calculated from European Commission fisheries statistics.

Fuel use / emissions	**2008**	**2009**	**2010**	**Average**
Fuel use (kt)	251.25	250.62	253.58	251.82
CO_2 (kt)	801.49	799.48	808.91	803.29
NO_X (kt)	19.72	19.67	19.91	19.77
CO (kt)	1.86	1.85	1.88	1.86
NMVOC (kt)	0.70	0.70	0.71	0.71
SO_X (kt)	5.03	5.01	5.07	5.04
PM (kt)	0.38	0.38	0.38	0.38

Table 6.5. Total fuel use and atmospheric pollution emissions from the UK fishing fleet from 12th May 2012 – 11th May 2013 calculated using an AIS-activity-based method.

Fuel use / emissions	**Total**	**Main**	**Auxiliary**	**Auxiliary (%)**
Fuel use (kt)	270.84	218.16	52.68	19
CO_2 (kt)	864.25	696.14	168.11	19
NO_X (kt)	14.14	10.86	3.28	23
CO (kt)	0.55	0.44	0.11	19
NMVOC (kt)	1.31	1.21	0.10	7
SO_X (kt)	2.00	1.61	0.39	19
PM (kt)	0.91	0.83	0.08	9

Table 6.6. Atmospheric pollution emissions from the UK fishing fleet by vessel type and Gross Tonnage (GT) produced using combined speed calculation methodology (12 May 2012 – 12 May 2013).

Vessel group	**CO_2 main + aux (kt)**	**NO_x main + aux (kt)**	**SO_2 main + aux (kt)**	**NMVOC main + aux (kt)**	**CO main + aux (kt)**	**PM main + aux (kt)**	**Fuel use main + aux (kt)**
Seiners (<100 GT)	1.029	0.016	0.001	0.002	0.002	0.001	0.322
Seiners (100 GT+)	12.043	0.204	0.008	0.016	0.028	0.011	3.774
Trawlers (<100 GT)	335.140	5.238	0.210	0.581	0.777	0.399	105.026
Trawlers (100 GT+)	470.681	7.968	0.295	0.631	1.092	0.444	147.502
Dredgers (<100 GT)	22.050	0.342	0.014	0.039	0.051	0.027	6.910
Dredgers (100 GT+)	5.476	0.092	0.003	0.008	0.013	0.005	1.716
Passive gear (<100 GT)	17.827	0.277	0.011	0.031	0.041	0.021	5.587
Passive gear (100 GT+)	0.000	0.000	0.000	0.000	0.000	0.000	0.000

6.4 Discussion

Calculating emissions using a bottom-up AIS activity-based approach produced marginally higher estimates of fuel use and emissions than those produced using a fuel-based approach based on European fisheries fuel consumption statistics. The fuel use calculated using the calibrated activity-based model (270.8 kt) are only 7.5% higher than the results of the fuel-based model (251.8 kt) for the UK fishing fleet over the year modelled. Compare this to the uncalibrated results presented in Chapter 5 of 325.4 kt (Table 5.10), which are a far more significant 29.5% higher than the fuel-based method. This demonstrates the importance of carefully selecting model input parameter.

The results of the fuel-based approach used in this study are close to an estimate produced using vessel operator surveys by Seafish, the UK fishing industry body, of 252 kt of fuel consumed annually by the UK fishing fleet (Curtis et al., 2006). This goes some way to validate the fuel-based methodology employed in this study and could suggest that the activity-based approach has produced a slight overestimate. However, the fact that that both approaches produce similar results, and that these results are close to those produced by Seafish, is indicative that both are capable of producing sensible results.

Ideally, it would be possible to compare the results produced during this study with other activity-based emissions inventories for the UK fishing fleet. However, the only example (Whall et al., 2010) does not present the results in a disaggregated format, meaning that emissions from fishing vessels alone cannot be interpreted.

The Third IMO GHG Study 2014 (Smith et al., 2014) only considers fishing vessels of 100 GT or more. The 22,130 fishing vessels included are modelled as producing 22 million tonnes of CO_2 in 2012, equating to an average of 994 tonnes of CO_2 per vessel. The average emissions calculated for the 427 vessels of 100 GT or more in this study were 1,143 tonnes of CO_2, 15% higher than the IMO average. This may, in part, be attributable to the detection of trawling and dredging activities and application of an adjusted engine load in this study. The results of the data analysis performed in Section 4.5 also indicated that the AIS data tracks associated with the UK show above average relative speed compared to the average of the study area as a whole (Table 4.1). This could also account for some of the variation from the IMO global average.

Another possible explanation for the discrepancy could be the use of activity sampling in the activity-based method. If, for example, AIS devices tend to be fitted to vessels that have higher than average levels of activity, then this would lead to an overestimate of emissions and fuel use by less active vessels in the fleet using the activity-based methodology presented. This is assuming that the fuel-based results are close to the real values. There is, however, significant variation in the fuel efficiency figures used in the fuel-based approach (Table 6.2), indicating that significant uncertainty exists in fuel-based approaches as well. Indeed, much of the research in the field of shipping emissions inventorying methodologies has concluded that fuel-based methods tend to underestimate atmospheric pollution emissions (Buhaug et al, 2009; Smith et al., 2014).

Other potential sources of the discrepancies relate to the parameterisation of the emissions model. In particular, the inputs to the engine load calculation formula have a significant influence on results, as shown in Chapter 5. The uncalibrated model results were produced using assumptions about idling/hotelling main engine load, sea margin and engine use while hotelling that were largely taken from the *EMEP/EEA air pollutant emission inventory guidebook 2016* (Trozzi et al., 2016) and the *Second IMO GHG Study 2009* (Buhaug et al., 2009). Alternative input values are available in the literature that were used to inform the selection of calibrated input parameters used in this chapter (Linstand et al., 2011; Smith et al., 2012), which seem to produce more realistic results.

The fact that the results produced using independent fuel-based and activity-based methods are similar indicates that both methods are viable for calculating atmospheric pollution emissions from small commercial vessels and activity-based methods should be considered for the other advantages that they offer. Although significant effort is involved in developing the software necessary to model shipping emissions using AIS data, once the modelling framework is in place, the time and effort involved in producing emissions inventories is minimal and does not rely on expensive and time-consuming activities such as surveying vessel operators.

For example, the software produced for this study could be reused to produce future emissions inventories for fishing vessels or other shipping sectors with minimal additional work as running the software with different input data would require essentially no additional work. The software could also be rerun periodically to produce updated emissions inventories as new AIS data became available. Also, unlike fuel-based estimates, the use of an AIS activity-based methodology enables the production of spatially and temporally resolved emission inventories that can easily be aggregated for any desired sub-group of vessels.

For example, emissions can be aggregated for vessels falling within defined categories of length, GT or engine power, and for different vessel types (e.g. Table 6.5). The aggregation of emissions by vessel category shows some degree of disagreement between the activity-based and fuel-based methodologies used. Both show trawlers to be responsible for the majority of fuel use and emissions. However, the activity-based method shows a much larger majority. This may, in part, be due to all vessels with secondary trawling gear being defined as trawlers in the activity-based methodology so that appropriate engine load override rules could be assigned.

Interestingly, the results of this study indicate that including only vessels over 100 GT would result in the omission of around 43.5% of atmospheric pollution emissions from the UK fishing fleet. This supports the estimate of emissions of fishing vessels omitted from shipping emissions inventories by Endresen et al. (2007).

The ability to produce temporally and spatially resolved emissions inventories is a significant advantage of the activity-based approach as it makes the results viable for use in chemical transport models to assess the impacts of pollution upon human health and the environment (Corbett et al., 2007; Dalsøren et al., 2009; Lauer et al., 2007; Winebrake et al., 2009; Jalkanen et al., 2014). The mapped results (Figure 3.11) show a plausible spatial distribution of emissions that would improve with any increase in the proportion of vessels within the fleet using AIS technology.

The major sources of uncertainty in this study, namely the lack of reliable vessel design speed data and the relatively small sample of activity data used are issues of data availability that can be expected to improve in the future. A survey of vessel manufactures or operators could yield the design speed data necessary. A larger proportion of fishing vessel operators can also be expected to voluntarily adopt AIS technology for the safety benefits it offers, leading to an increased sample size of activity data. Engine load may also be calculated using a more sophisticated and accurate methodology through prediction of required power at a particular speed in calm water and in waves, provided that sufficient vessel parameters are known (Dedes, 2013).

The use of satellite AIS data may also improve the coverage of the data captured for vessels operating outside of terrestrial AIS network range. However, the lower signal strength of messages broadcast by the Class-B AIS devices used by small commercial and recreational vessels may not be powerful enough for reliable detection by AIS satellites (Taylor-Branco, 2013).

Ultimately, this study builds upon previous work that has used AIS data for the calculation of emissions inventories and specifically addresses some of the issues that must be tackled when calculating emissions from small commercial vessels. The challenges of sampling activity for fleets with less than 100% AIS technology uptake in a way that allows emissions to be spatially allocated without the use of supplementary data, uncertainty of engine and fuel type used and the requirement to detect and correct special engine load conditions for vessels engaged in towing and pushing operations will also apply to other types of small commercial and vessel such as tugs.

6.5 Conclusions

A new bottom-up activity-based atmospheric emissions modelling approach has been trialled using the case study fleet of UK fishing vessels. While the efforts at validating the methodology against an independent fuel-based approach and comparable published emissions inventories indicates that the methodology produces sensible results when input parameters are calibrated, more effort is still needed to validate the methodology presented more thoroughly.

Nevertheless, the use of a bottom-up activity-based methodology that makes use of AIS data offers numerous advantages over commonly used fuel-based methods. This methodology is the first that can accommodate special operating modes such as trawling and dredging, which is a necessity when modelling emissions from fishing vessels. It also offers a solution for modelling emissions for fleets of vessels that do not have full uptake of AIS devices that appears to produce reasonable results.

Given that small commercial vessels under 100 GT tend to be omitted from shipping emissions inventories, the methodology outlined here could be used to complement existing AIS activity-based approaches for the inclusion of emissions from vessels under 100 GT in emissions inventories. The results of this case study suggest that, for fishing vessels at least, upward of 40% of emissions are missed from emissions inventories if vessels under 100 GT are excluded.

7 Conclusions

Small commercial watercraft are generally omitted from inventories of atmospheric emissions from the shipping industry. This omission is likely to result in a significant underrepresentation of emissions from the shipping sector and hampering the creation of mitigation measures targeting this group of vessels. The aim of this project was to develop a methodology that can be used to address the omission of small commercial watercraft from shipping emissions inventories. A summary of the conclusions related to each of the objectives of this project is presented below. The key contributions of this work are then listed and areas for future work are suggested.

7.1 Objective 1: To review previously used methodologies for the production of atmospheric emissions inventories for shipping activities and assess their applicability to small commercial watercraft.

A comprehensive review of the literature was undertaken to identify and categorize the methodologies that have been used to create inventories of atmospheric emissions from ships (Chapter 2). A general trend is apparent in the literature of inventory compilers moving from fuel-based methods to the use of increasingly sophisticated activity-based approaches. The current state-of-the-art in the field is the use AIS data to produce highly detailed and accurate spatially- and temporally-resolved emissions inventories, where the fuel use and atmospheric emissions of each vessel under consideration are individually modelled.

AIS data, collected and archived by the operators of coastal and satellite receivers, provides a wealth of information about vessel activities that can be used to produce high-quality emissions inventories. However, AIS datasets are extremely large and can contain significant errors. Using these data to calculate emissions inventories is a considerable software engineering challenge, especially when looking to achieve the performance necessary to undertake uncertainty and sensitivity analysis.

Reviewing the literature also revealed that very little research had been undertaken to quantify emissions caused by small commercial vessels. It is thought that this omission could amount to as much as 10% of emissions from global shipping activities. These vessels are commonly omitted from inventories of shipping emissions due to a lack of available data and methods that would make their inclusion practicable. However, an increasing number of small commercial vessel operators are utilizing AIS technology, creating an opportunity to use the data produced to model the emissions from these vessels. Doing so will, however, require overcoming some challenges such as dealing with fleets for which only a subset of vessels use AIS technology and where the necessary data to directly link vessels to the AIS data they produce is not readily available.

7.2 Objective 2: To create a robust, repeatable and practical methodology for the calculation of atmospheric pollution caused by small commercial watercraft.

The main outcome of this project has been the development of a methodology and software tool that can be used to calculate emissions inventories for small commercial watercraft using AIS data. The source code for this tool is available in the accompanying electronic materials. The results produced can be disaggregated by vessel type and size categories, temporally resolved to identify changing activity throughout the year and mapped to show the geographic distribution of emissions (Chapter 3).

The methodology developed has a number of novel features. Previous work has either used the speed data stored in AIS messages broadcast by vessels or a speed based on the distance over ground and time between AIS data points. A combined approach is introduced, using the distance over ground as a lower bound and, when higher, the speeds reported in the AIS data as the upper bound to a range of values representing the vessel's likely speed (Section 3.3.5, 3.3.4 and 5.4).

An approach was developed for the detection of special vessel operating condition, such as trawling and dredging by fishing vessels, so that an appropriate engine load can be assigned (Section 3.3.5). An adaptation of a simple formula for estimating engine load from vessel speed was also developed that scales engine load between engine loads while idling and cruising at design speed based on the vessel's instantaneous speed (Section 3.3.3).

A novel AIS sampling approach was developed and refined (Chapter 4). Using this methodology, it is possible to calculate emissions for fleets of vessels where a one-to-one matching of vessel technical information with AIS data records is not practicable. This can be the case when the data required to match vessels to AIS records is unavailable, or because some of the vessels being modelled are not fitted with AIS devices and, therefore, do not produce AIS data. These conditions typify fleets of small commercial vessels, so a robust activity sampling methodology is crucial if AIS data are to be used to produce emissions inventories for these vessels.

Testing of different filtering criteria for constraining the AIS tracks available for sampling showed that unwanted bias could be inadvertently introduced by attempting to stratify sampling based on vessel length (Section 4.6). Vessel size was also shown to be a poor predictor of activity profile (Section 4.4). Grouping tracks by the countries that they visit showed that, despite being a largely domestic activity, many fishing vessels visit the ports of multiple countries. It also showed that the fleets associated with different countries in the study area had significantly different activity metrics, highlighting the importance of geographical relevance when sampling AIS tracks to represent vessel activity.

For the case study fleet of UK fishing vessels, a set of sampling criteria were developed that balanced the need for AIS track quality, relevance to the UK and the need to retain a sufficient number of tracks for representation of the fleet's activity. This resulted in a sampling pool of AIS tracks representing a number of vessels equivalent to 10.1% of the case study fleet of UK fishing vessels. It was also found that a minimum of 20, and preferably 30, AIS tracks should be sampled for each vessel to limit the risk of potential overrepresentation of certain AIS tracks in results.

7.3 Objective 3: To identify sources of uncertainty that affect the emissions calculation methodology developed and undertake a rigorous sensitivity and uncertainty analysis.

A detailed sensitivity and uncertainty analysis was undertaken, the results of which are presented in Chapter 5. The sources of structural, epistemic and aleatory uncertainty affecting the model were identified (Table 5.2). To carry out the number of model reuls required to conduct uncertainty and sensitivity analysis, the software used to calculate emissions needed to be highly optimised. This adds significantly to the software engineering challenge associated with calculating emissions inventories using AIS data.

Comparison of speed calculation methods indicates that this is an important decision in AIS-based emissions calculation methodologies and can have a significant influence on results (Section 5.4.1). This topic also tends to receive little attention from researchers. The combined speed calculation method introduced in this project, in addition to utilising more of the available data in AIS messages to estimate vessel speed, generates a range of possible values for a vessel's instantaneous speed for each AIS track segment. This goes some way towards capturing the uncertainty around vessel instantaneous speed and can be used in uncertainty analysis (Section 5.4.1).

Sampling AIS tracks appears to be the dominant source of uncertainty, but still yields reasonably stable results that are within ±3.5% of the mean with a 95% confidence interval for all pollutants. Emission factors are found to be the second most significant source of uncertainty. However, both of these sources of uncertainty were found to add roughly symmetrical uncertainty around the mean. It is the sources of uncertainty that may introduce bias to the mean results that are of greater importance.

It was found that the input parameters contributing to engine load calculation (main engine hotelling/idling load, sea margin and vessel design speed) can introduce significant systematic bias to results. Therefore, the selection of these parameters should be undertaken with care and, where possible, parameters should be calibrated using other sources of information on fleet fuel use and emissions to ensure that sensible results are produced.

The results of a Monte Carlo uncertainty analysis shows that results are relatively stable with a variation from the mean of less than ±6% for all modelled emissions and fuel use at the 95% confidence interval. This suggests that results are reasonably stable even when using sampled AIS activity data and fleet level averages for the proportions of engine and fuel types used. This is important as it suggests that using an activity-sampling approach such as the one developed for this project is a viable solution for modelling emissions from fleets where direct one-to-one matching of vessels to AIS data is not feasible, e.g. fleets of small commercial vessels.

7.4 Objective 4: To calculate an emissions inventory for a case study fleet of small commercial vessels and assess the validity of results.

In order to develop and test the methodology and software created, a case study fleet of small commercial vessels was required. Analysis of available data sources revealed that the European Commission maintain the European Commission Community Fishing Fleet

Register (ECCFFR), a database of fishing vessels containing much of the vessel specification information required as inputs to the activity-base emissions calculation methodology. A case study year of AIS data for fishing vessel operating in the seas of North-Western Europe was obtained via the *MarineTraffic.com* researcher network.

Emissions were calculated for the case study fleet of UK fishing vessels using the new AIS-based methodology and software developed during this research. An alternative fuel-based methodology was also developed and used to corroborate the results of the AIS-based methodology. The results produced (Section 6.3) indicated that the AIS-based approach, when using appropriately calibrated input parameters, yields estimates of annual fuel consumption (270.8 kt) that are similar to the fuel-based methodology (251.8 kt). Both sets of results were within a reasonable margin or error compared to the few sources of comparable published emissions estimates to suggest that the methodology developed produces believable results.

The use of an activity-based approach also enabled the comparison of emissions from different categories of vessel. Comparison of emissions from vessels of different sizes suggested that 43.5% of fuel use and CO_2 emissions from the UK fishing fleet are produced by vessels under 100 GT in size. This supports the suggestion that the omission of small commercial vessels from global emissions inventories could result in a significant underestimation of emissions from some shipping sectors. Given the feasibility of using AIS data to estimate emissions from small commercial vessels using methodologies such as the one described in this thesis, it seems reasonable to hope that such a methodology will be adopted in order to include small commercial watercraft when global and national shipping emissions inventories are calculated in the future.

7.5 Contribution

1. This is the first research that has specifically tackled the use of AIS data to produce emissions inventories for small commercial watercraft.
2. The case study emissions inventory is the most complete activity-based emissions inventory produced for the UK fishing fleet.
3. The sampling methodology used to associate vessels with AIS data is novel, produces reasonable results, and can be used to model emissions of vessels that either do not have AIS devices or where insufficient data are available to match vessels with AIS data.
4. This is the first methodology to use a combination of both distance-based and AIS speed based methods to calculate vessel instantaneous speed from AIS data. The speed method used is shown to have a significant effect upon results. The combined approach shows promise for use in uncertainty analysis.
5. This is the first methodology to use AIS data to detect when vessels are engaged in trawling and dredging activities and apply a corrected engine load.
6. The sensitivity and uncertainty analysis undertaken as a part of this research contributes useful insight to the factors that affect the validity and accuracy of shipping emissions inventories calculated using activity-based methods. The importance of carefully selecting the parameters contributing to engine load calculation is highlighted given the bias in results that can arise due to these parameters.

7.6 Publications arising from this project

Coello, J., Williams I., Hudson, D., Kemp, S. (2015) An AIS-based approach to calculate atmospheric emissions from the UK fishing fleet. *Atmospheric Environment,* 114.

A copy of this article is available in the accompanying electronic material. As of March 2018, it has been cited 7 times.

7.7 Future work

The methodology and software delivered in this project open up a number of potential areas for future research. These can be broadly categorised as:

- Data collection for better model parameterisation and validation,
- Application of the methods and software to other fleets and new AIS data,
- Investigation of emissions allocation approaches,
- Improvements of the methodology to improve accuracy,
- Extension of the methodology to enable the simulation of mitigation measures.

7.7.1 Data collection for model parameterisation and validation

An effort has been made to thoroughly review the literature for model input parameters and to validate model results against an alternative calculation methodology and comparable published data. However, the accuracy of the results could be improved by working with vessel manufacturers, maintainers and operators to gather additional vessel data, such as design speed and specific engine technology, and to develop input parameters to the model that are specifically tailored to the type of vessels being modelled. The parameters for engine idling load, sea margin, auxiliary engine loads throughout all operating modes, and engine usage while vessels are stopped all have a significant impact upon results and could be improved by collecting additional data.

Working with vessel operators could also provide valuable data to further validate the results of the AIS-based activity model. Greater confidence in the core emissions calculation methodology and a better quantification of uncertainty could be achieved by obtaining vessel fuel consumption data from vessel operators and comparing that to fuel use modelled using AIS data produced by those vessels.

7.7.2 Application of the methods and software to other fleets

A natural extension of this work would be the application of the methodology and software to produce emissions inventories for new fleets of vessels. For example, the software could be used to produce an emissions inventory for the European or international fishing fleets. The use of satellite AIS data could also be used to improve modelling of vessel activities and emissions away from shores.

The emissions calculation methodology developed should also be well suited for use with other types of small commercial vessels such as tugs, workboats and small passenger vessels. By obtaining additional AIS data and identifying vessel characteristics datasets for these other types of small commercial vessel, this methodology could be used to estimate the emissions that they produce.

7.7.3 Emissions allocation

This project was focused predominantly on the methodologies required for the calculation of emission. The allocation of those emissions to nations and regions was outside of the scope of work. When dealing with small commercial watercraft, emissions allocation will often be simpler than for vessels engaged in international shipping activities because the majority of small commercial vessel types are usually engaged in domestic activities. This is the case for fishing vessels, and so the assumption that emissions can be allocated to the vessel's flag nation is considered to be more valid than for large vessels that operate internationally.

However, visits to other nations do occur, as was observed in the AIS data used in this project. Therefore, consideration should be given to the validity of the assumption that emissions can be allocated to the vessel's flag nation and, if necessary, alternative allocation approaches should be developed. The use of AIS data and a methodology such as the one developed in this project to empirically identify where vessels operate and the ports that they visit could provide valuable information for this debate as well as the mechanism to implement the emissions allocation approaches developed.

7.7.4 Improvements to the methodology

At the core of the methodology developed is a very simple formula for estimating engine load from vessel instantaneous speed as a ratio of design speed. This is an adaption of a common approach used in previous shipping emissions calculation methodologies. However, this engine load estimation methodology is relatively crude and does not effectively differentiate between calm water and rougher conditions. More accurate methods can be employed if sufficient vessel characteristics data can be obtained, which enable more accurate estimation of power requirements in calm water and waves, e.g. Dedes (2013).

Furthermore, this and the majority of other shipping emissions inventory calculation methodologies do not model the effect of tides and weather conditions on vessel power requirements, engine load and emissions. The methodology could be improved through the incorporation of these factors to more fully capture the operating conditions of the vessels being modelled and the use of a more sophisticated engine load calculation methodology that captures the effect of these additional factors.

7.7.5 Extension of the methodology to enable the simulation of mitigation measures

One of the advantages of bottom-up activity-based emissions calculation methodologies is their potential for simulating technological and operational measures that could be employed to reduce fuel consumption and pollution emissions. Certain measures could be simulated without extension of the software by changing vessel specification, e.g. engine type, or by changing emission factors, e.g. to reflect changes in fuel sulphur content. Other technical measures, such as the use of diesel-electric drive or hybrid propulsion systems requires more subtle modelling of vessels and their dynamic power requirements. This is something that can be done using a bottom-up activity-based approach and could be incorporated into the methodology and software produced in this project with some additional research effort.

Another area where bottom-up activity-based methodologies can be used to simulate mitigation measures is in capturing the potential changes in vessel operating practices. For example, slow steaming is an effective way to make substantial reductions in fuel consumption and atmospheric emissions. Similarly, minimising the variation in cruising speed over a journey will also result in a lower average engine load. These operational measures could also be simulated using the software developed with some additional model development.

7.8 Final remarks

This thesis has presented several novel contributions, including a methodology for the use of AIS data in calculating emissions inventories for fleets of small commercial vessels; the introduction of novel methods for sampling AIS data for vessels that cannot be directly associated with AIS data records; the treatment of uncertainty in the speed calculated from AIS data through the introduction of a new combined speed calculation method; and the addition of engine load override rules for detecting and modelling emissions of vessels engaged in towing and pushing activities. The results calculated for the case-study also constitute a detailed and spatially disaggregated emissions inventory of UK fishing activities. Finally, the treatment of sensitivity and uncertainty provides useful insight in to the model parameters that can produce systematic bias in results, as well as those that produce unbiased uncertainty in results.

The software developed in the course of this research is a fast, powerful and flexible tool for the calculation of fuel use and atmospheric pollution emissions from shipping activities and makes significant progress in the applicability of AIS-based emissions calculation methods to fleets of small commercial vessels. The availability of data sources like AIS creates fantastic opportunities for research into shipping activities. However, the development of the tooling and techniques for its use present a significant overhead to the research community. It is hoped that the work undertaken throughout this project will serve to reduce that overhead for other researchers in the future.

Appendix A

Table A.1. Sample pool characteristics with varying filtering criteria for all AIS tracks in the study area (AIS tracks defined as all AIS data points with a particular MMSI number).

				Mean activity metrics			
Min. AIS data points	**Min. duration (yrs)**	**Max error segments (%)**	**Tracks**	**Error segments (%)**	**Moving (%)**	**Relative speed**	**Relative speed (moving)**
2	0	1	5061	5.29%	72.70%	0.226	0.293
2	0	0.25	4904	3.54%	72.71%	0.223	0.289
2	0	0.1	4552	2.67%	72.18%	0.215	0.282
2	0	0.05	3818	1.83%	70.43%	0.200	0.269
2	0	0.01	1211	0.56%	58.57%	0.155	0.244
2	0.25	1	4200	4.57%	73.24%	0.211	0.274
2	0.25	0.25	4110	3.43%	73.22%	0.208	0.270
2	0.25	0.1	3845	2.68%	72.71%	0.201	0.263
2	0.25	0.05	3232	1.87%	70.99%	0.187	0.252
2	0.25	0.01	966	0.61%	58.63%	0.130	0.211
2	0.5	1	3764	4.17%	73.05%	0.204	0.265
2	0.5	0.25	3705	3.34%	73.07%	0.201	0.262
2	0.5	0.1	3485	2.64%	72.62%	0.195	0.256
2	0.5	0.05	2951	1.86%	70.95%	0.182	0.245
2	0.5	0.01	879	0.62%	59.01%	0.125	0.203
2	0.75	1	3299	3.67%	72.79%	0.196	0.258
2	0.75	0.25	3270	3.26%	72.77%	0.195	0.256
2	0.75	0.1	3087	2.61%	72.28%	0.189	0.250
2	0.75	0.05	2628	1.86%	70.57%	0.176	0.239
2	0.75	0.01	784	0.63%	58.30%	0.118	0.197
2	1	1	1762	2.75%	67.86%	0.157	0.224
2	1	0.25	1755	2.56%	67.86%	0.156	0.222
2	1	0.1	1714	2.29%	67.72%	0.155	0.221
2	1	0.05	1527	1.73%	66.37%	0.145	0.213
2	1	0.01	506	0.62%	53.77%	0.096	0.178
500	0	1	4306	3.07%	71.72%	0.200	0.267
500	0	0.25	4295	2.94%	71.74%	0.200	0.266

				Mean activity metrics			
Min. AIS data points	**Min. duration (yrs)**	**Max error segments (%)**	**Tracks**	**Error segments (%)**	**Moving (%)**	**Relative speed**	**Relative speed (moving)**
500	0	0.1	4135	2.53%	71.48%	0.198	0.264
500	0	0.05	3560	1.82%	70.09%	0.188	0.256
500	0	0.01	1117	0.60%	58.31%	0.136	0.225
500	0.25	1	3866	3.15%	72.35%	0.197	0.260
500	0.25	0.25	3855	3.01%	72.37%	0.196	0.259
500	0.25	0.1	3703	2.57%	72.10%	0.194	0.257
500	0.25	0.05	3170	1.85%	70.61%	0.183	0.248
500	0.25	0.01	962	0.61%	58.46%	0.128	0.210
500	0.5	1	3537	3.15%	72.37%	0.192	0.255
500	0.5	0.25	3526	2.99%	72.39%	0.192	0.254
500	0.5	0.1	3388	2.56%	72.12%	0.189	0.251
500	0.5	0.05	2908	1.84%	70.61%	0.179	0.243
500	0.5	0.01	875	0.62%	58.82%	0.123	0.202
500	0.75	1	3165	3.12%	72.25%	0.188	0.250
500	0.75	0.25	3156	2.98%	72.28%	0.188	0.249
500	0.75	0.1	3033	2.56%	71.99%	0.185	0.246
500	0.75	0.05	2607	1.84%	70.40%	0.173	0.237
500	0.75	0.01	783	0.63%	58.25%	0.118	0.196
500	1	1	1753	2.69%	67.79%	0.155	0.222
500	1	0.25	1747	2.53%	67.81%	0.155	0.221
500	1	0.1	1711	2.29%	67.69%	0.154	0.220
500	1	0.05	1525	1.73%	66.35%	0.145	0.213
500	1	0.01	506	0.62%	53.77%	0.096	0.178
1000	0	1	3960	2.79%	71.07%	0.191	0.257
1000	0	0.25	3954	2.71%	71.08%	0.190	0.257
1000	0	0.1	3849	2.43%	70.85%	0.189	0.256
1000	0	0.05	3358	1.78%	69.64%	0.180	0.249
1000	0	0.01	1086	0.59%	58.02%	0.131	0.219
1000	0.25	1	3656	2.86%	71.67%	0.189	0.253
1000	0.25	0.25	3650	2.77%	71.68%	0.189	0.253
1000	0.25	0.1	3548	2.48%	71.44%	0.187	0.252

				Mean activity metrics			
Min. AIS data points	**Min. duration (yrs)**	**Max error segments (%)**	**Tracks**	**Error segments (%)**	**Moving (%)**	**Relative speed**	**Relative speed (moving)**
1000	0.25	0.05	3081	1.81%	70.16%	0.179	0.244
1000	0.25	0.01	957	0.61%	58.26%	0.126	0.209
1000	0.5	1	3373	2.87%	71.88%	0.186	0.249
1000	0.5	0.25	3367	2.77%	71.90%	0.186	0.249
1000	0.5	0.1	3274	2.48%	71.65%	0.184	0.247
1000	0.5	0.05	2847	1.82%	70.33%	0.175	0.239
1000	0.5	0.01	872	0.62%	58.68%	0.122	0.201
1000	0.75	1	3039	2.87%	71.81%	0.183	0.245
1000	0.75	0.25	3033	2.77%	71.83%	0.183	0.245
1000	0.75	0.1	2952	2.49%	71.59%	0.181	0.243
1000	0.75	0.05	2566	1.83%	70.19%	0.171	0.234
1000	0.75	0.01	781	0.63%	58.15%	0.117	0.196
1000	1	1	1729	2.54%	67.73%	0.154	0.221
1000	1	0.25	1725	2.43%	67.72%	0.154	0.220
1000	1	0.1	1700	2.26%	67.56%	0.153	0.219
1000	1	0.05	1521	1.72%	66.29%	0.145	0.212
1000	1	0.01	506	0.62%	53.77%	0.096	0.178
5000	0	1	2724	1.97%	67.20%	0.153	0.223
5000	0	0.25	2722	1.94%	67.19%	0.153	0.222
5000	0	0.1	2707	1.88%	67.21%	0.153	0.222
5000	0	0.05	2544	1.58%	66.78%	0.151	0.221
5000	0	0.01	933	0.60%	57.65%	0.117	0.198
5000	0.25	1	2675	1.99%	67.23%	0.153	0.223
5000	0.25	0.25	2673	1.96%	67.23%	0.153	0.222
5000	0.25	0.1	2658	1.90%	67.24%	0.153	0.222
5000	0.25	0.05	2495	1.60%	66.81%	0.151	0.221
5000	0.25	0.01	905	0.61%	57.31%	0.116	0.198
5000	0.5	1	2554	2.02%	67.65%	0.153	0.221
5000	0.5	0.25	2552	1.99%	67.64%	0.152	0.221
5000	0.5	0.1	2537	1.93%	67.66%	0.152	0.220
5000	0.5	0.05	2378	1.62%	67.22%	0.150	0.219

				Mean activity metrics			
Min. AIS data points	**Min. duration (yrs)**	**Max error segments (%)**	**Tracks**	**Error segments (%)**	**Moving (%)**	**Relative speed**	**Relative speed (moving)**
5000	0.5	0.01	840	0.62%	57.88%	0.115	0.193
5000	0.75	1	2349	2.03%	67.85%	0.152	0.220
5000	0.75	0.25	2347	2.00%	67.84%	0.152	0.219
5000	0.75	0.1	2332	1.93%	67.86%	0.152	0.219
5000	0.75	0.05	2192	1.64%	67.38%	0.150	0.217
5000	0.75	0.01	760	0.63%	57.57%	0.112	0.191
5000	1	1	1545	2.06%	65.68%	0.139	0.208
5000	1	0.25	1543	2.01%	65.66%	0.139	0.207
5000	1	0.1	1534	1.95%	65.66%	0.138	0.207
5000	1	0.05	1435	1.64%	65.10%	0.135	0.205
5000	1	0.01	504	0.62%	53.80%	0.096	0.177

Table A.2. Sample pool characteristics with varying filtering criteria for AIS tracks with at least 10% of port stops at UK ports (AIS tracks defined as all AIS data points with a particular MMSI number).

				Mean activity metrics			
Min. AIS data points	**Min. duration (yrs)**	**Max error segments (%)**	**Tracks**	**Error segments (%)**	**Moving (%)**	**Relative speed**	**Relative speed (moving)**
2	0	1	877	3.74%	74.38%	0.204	0.267
2	0	0.25	864	2.76%	74.66%	0.204	0.267
2	0	0.1	841	2.42%	74.66%	0.202	0.265
2	0	0.05	746	1.87%	74.19%	0.197	0.260
2	0	0.01	214	0.61%	64.92%	0.133	0.217
2	0.25	1	775	3.49%	76.95%	0.210	0.265
2	0.25	0.25	766	2.71%	77.12%	0.210	0.265
2	0.25	0.1	747	2.42%	77.03%	0.208	0.263
2	0.25	0.05	666	1.90%	76.40%	0.203	0.260
2	0.25	0.01	180	0.64%	66.44%	0.131	0.206
2	0.5	1	707	3.29%	76.92%	0.207	0.261
2	0.5	0.25	700	2.71%	76.88%	0.206	0.260
2	0.5	0.1	682	2.41%	76.81%	0.204	0.258
2	0.5	0.05	610	1.91%	75.87%	0.198	0.255
2	0.5	0.01	166	0.65%	65.99%	0.127	0.200
2	0.75	1	610	3.19%	77.38%	0.208	0.261
2	0.75	0.25	605	2.72%	77.36%	0.207	0.260
2	0.75	0.1	589	2.39%	77.21%	0.204	0.257
2	0.75	0.05	530	1.92%	76.32%	0.198	0.253
2	0.75	0.01	136	0.66%	66.02%	0.126	0.200
2	1	1	297	2.57%	73.78%	0.179	0.237
2	1	0.25	296	2.24%	73.84%	0.178	0.234
2	1	0.1	294	2.16%	73.93%	0.178	0.234
2	1	0.05	272	1.77%	73.32%	0.175	0.234
2	1	0.01	78	0.64%	61.82%	0.106	0.184
500	0	1	810	2.72%	75.24%	0.200	0.260
500	0	0.25	808	2.48%	75.28%	0.200	0.259
500	0	0.1	797	2.33%	75.29%	0.199	0.259

				Mean activity metrics			
Min. AIS data points	**Min. duration (yrs)**	**Max error segments (%)**	**Tracks**	**Error segments (%)**	**Moving (%)**	**Relative speed**	**Relative speed (moving)**
500	0	0.05	716	1.84%	74.81%	0.196	0.257
500	0	0.01	206	0.61%	65.65%	0.130	0.208
500	0.25	1	742	2.76%	76.72%	0.205	0.262
500	0.25	0.25	740	2.51%	76.77%	0.205	0.261
500	0.25	0.1	730	2.36%	76.72%	0.204	0.260
500	0.25	0.05	656	1.88%	76.15%	0.201	0.259
500	0.25	0.01	179	0.64%	66.26%	0.131	0.206
500	0.5	1	681	2.80%	76.48%	0.202	0.257
500	0.5	0.25	679	2.52%	76.54%	0.201	0.256
500	0.5	0.1	669	2.36%	76.48%	0.200	0.255
500	0.5	0.05	602	1.89%	75.63%	0.197	0.254
500	0.5	0.01	165	0.65%	65.79%	0.127	0.200
500	0.75	1	593	2.84%	76.97%	0.203	0.257
500	0.75	0.25	591	2.52%	77.04%	0.202	0.256
500	0.75	0.1	582	2.35%	77.00%	0.201	0.255
500	0.75	0.05	527	1.91%	76.20%	0.197	0.253
500	0.75	0.01	136	0.66%	66.02%	0.126	0.200
500	1	1	297	2.57%	73.78%	0.179	0.237
500	1	0.25	296	2.24%	73.84%	0.178	0.234
500	1	0.1	294	2.16%	73.93%	0.178	0.234
500	1	0.05	272	1.77%	73.32%	0.175	0.234
500	1	0.01	78	0.64%	61.82%	0.106	0.184
1000	0	1	769	2.62%	75.50%	0.197	0.256
1000	0	0.25	767	2.37%	75.55%	0.197	0.255
1000	0	0.1	758	2.24%	75.51%	0.196	0.255
1000	0	0.05	691	1.82%	75.22%	0.194	0.253
1000	0	0.01	203	0.62%	65.95%	0.129	0.203
1000	0.25	1	719	2.69%	76.37%	0.201	0.258
1000	0.25	0.25	717	2.42%	76.42%	0.201	0.257
1000	0.25	0.1	708	2.28%	76.39%	0.200	0.257
1000	0.25	0.05	645	1.86%	76.00%	0.199	0.256
1000	0.25	0.01	179	0.64%	66.26%	0.131	0.206

				Mean activity metrics			
Min. AIS data points	**Min. duration (yrs)**	**Max error segments (%)**	**Tracks**	**Error segments (%)**	**Moving (%)**	**Relative speed**	**Relative speed (moving)**
1000	0.5	1	664	2.72%	76.24%	0.199	0.255
1000	0.5	0.25	662	2.44%	76.30%	0.198	0.254
1000	0.5	0.1	653	2.28%	76.26%	0.198	0.253
1000	0.5	0.05	595	1.87%	75.61%	0.195	0.253
1000	0.5	0.01	165	0.65%	65.79%	0.127	0.200
1000	0.75	1	579	2.77%	76.80%	0.200	0.254
1000	0.75	0.25	577	2.44%	76.86%	0.199	0.253
1000	0.75	0.1	569	2.29%	76.85%	0.199	0.253
1000	0.75	0.05	521	1.90%	76.23%	0.196	0.252
1000	0.75	0.01	136	0.66%	66.02%	0.126	0.200
1000	1	1	295	2.56%	73.71%	0.177	0.234
1000	1	0.25	294	2.23%	73.77%	0.176	0.232
1000	1	0.1	292	2.15%	73.86%	0.176	0.232
1000	1	0.05	270	1.75%	73.24%	0.173	0.231
1000	1	0.01	78	0.64%	61.82%	0.106	0.184
5000	0	1	529	1.75%	72.80%	0.169	0.231
5000	0	0.25	529	1.75%	72.80%	0.169	0.231
5000	0	0.1	528	1.73%	72.87%	0.169	0.231
5000	0	0.05	503	1.51%	72.57%	0.170	0.233
5000	0	0.01	181	0.63%	65.88%	0.125	0.198
5000	0.25	1	518	1.77%	73.03%	0.170	0.232
5000	0.25	0.25	518	1.77%	73.03%	0.170	0.232
5000	0.25	0.1	517	1.75%	73.11%	0.170	0.232
5000	0.25	0.05	492	1.53%	72.81%	0.171	0.234
5000	0.25	0.01	174	0.64%	65.88%	0.125	0.200
5000	0.5	1	494	1.80%	72.77%	0.168	0.230
5000	0.5	0.25	494	1.80%	72.77%	0.168	0.230
5000	0.5	0.1	493	1.78%	72.84%	0.168	0.230
5000	0.5	0.05	468	1.54%	72.52%	0.169	0.232
5000	0.5	0.01	162	0.64%	65.42%	0.123	0.197
5000	0.75	1	439	1.82%	73.31%	0.171	0.231
5000	0.75	0.25	439	1.82%	73.31%	0.171	0.231

				Mean activity metrics			
Min. AIS data points	**Min. duration (yrs)**	**Max error segments (%)**	**Tracks**	**Error segments (%)**	**Moving (%)**	**Relative speed**	**Relative speed (moving)**
5000	0.75	0.1	438	1.80%	73.40%	0.171	0.231
5000	0.75	0.05	419	1.59%	73.12%	0.172	0.234
5000	0.75	0.01	135	0.65%	65.77%	0.123	0.198
5000	1	1	257	1.87%	71.78%	0.157	0.216
5000	1	0.25	257	1.87%	71.78%	0.157	0.216
5000	1	0.1	256	1.83%	71.92%	0.157	0.216
5000	1	0.05	243	1.59%	71.78%	0.158	0.218
5000	1	0.01	78	0.64%	61.82%	0.106	0.184

Table A.3. Sample pool characteristics with varying minimum proportion of track stops at UK ports. Tracks filtered for a minimum of 1000 AIS points, 0.5 years duration and errors in a maximum of 10% of track segments. (AIS tracks defined as all AIS data points with a particular MMSI number).

		Mean activity metrics				
Min. proportion port stops at UK ports	**Tracks**	**Error segments (%)**	**Moving (%)**	**Relative speed**	**Relative speed (moving)**	**Port stops at UK ports (%)**
0.01	818	2.20%	73.87%	19.07%	25.37%	63.77%
0.05	723	2.28%	75.09%	19.42%	25.37%	71.82%
0.1	653	2.28%	76.26%	19.78%	25.34%	78.75%
0.25	558	2.26%	77.68%	20.37%	25.50%	89.47%
0.5	504	2.26%	77.49%	20.58%	25.74%	95.23%
1.0	353	2.34%	79.36%	21.61%	26.17%	100.00%

Appendix B

Table B.1. Fuel efficiency figures for beam trawlers compiled from European Scientific Fishery Data (after EC, 2013b). Fuel efficiency is expressed in litres of fuel (L) used per kilogram (kg) of catch landed.

Country	**< 12 m**			**12 - 24 m**			**24 - 40 m**			**40+ m**		
	2008	**2009**	**2010**	**2008**	**2009**	**2010**	**2008**	**2009**	**2010**	**2008**	**2009**	**2010**
Belgium				2.15	2.12	1.87	2.32	3.25	2.71			
diff. from UK				***0.35***	***0.06***		***1.11***	***1.48***				
Bulgaria												
Cyprus												
Denmark				0.96	0.97	0.80						
diff. from UK				***0.84***	***1.09***							
Estonia												
Finland												
France												
Germany	1.06	0.53	0.44	0.76	0.62	0.70	1.83	1.25	1.37			
diff. from UK				***1.04***	***1.44***		***0.62***	***0.52***				
Greece												
Ireland							4.62	4.55	2.15			
diff. from UK							**3.41**	**2.78**				
Italy				2.93	3.32	3.48	3.36	3.01	2.52			
diff. from UK				***1.13***	***1.26***		***2.15***	***1.24***				
Latvia												
Lithuania												
Malta												
Netherlands				1.20	1.24	1.06	3.19	2.18	2.01	3.01	2.87	2.37
diff. from UK				***0.60***	***0.82***		***1.98***	***0.41***				
Poland												
Portugal												
Romania												
Slovenia												
Spain												
Sweden												
United Kingdom (UK)				1.80	2.06		1.21	1.77				

Table B.2. Fuel efficiency figures for demersal trawlers and/or seiners compiled from European Scientific Fishery Data (after EC, 2013b). Fuel efficiency is expressed in litres of fuel (L) used per kilogram (kg) of catch landed.

Country	< 12 m			12 - 24 m			24 - 40 m			40+ m		
	2008	2009	2010	2008	2009	2010	2008	2009	2010	2008	2009	2010
Belgium						2.30		1.90	1.62			
diff. from UK								***0.98***				
Bulgaria												
Cyprus												
Denmark	0.17	0.15	0.07	0.29	0.22	0.21	0.18	0.18	0.19	0.08	0.07	0.07
diff. from UK	***0.77***	***0.79***		***0.73***	***0.75***		***0.74***	***0.74***		***0.60***	***0.67***	
Estonia												
Finland												
France	0.80	1.32	1.48	1.48	1.49	1.47	1.18	1.48	1.36			
diff. from UK	***0.14***	***0.38***		***0.46***	***0.52***		***0.26***	***0.56***				
Germany	0.31	0.28	0.18	0.32	0.25	0.33	0.16	0.15	0.30	0.75	0.66	0.60
diff. from UK	***0.63***	***0.66***		***0.70***	***0.72***		***0.76***	***0.77***		***0.07***	***0.08***	
Greece												
Ireland				1.66	1.18	0.81	1.12	0.99	0.74			
diff. from UK				***0.64***	***0.21***		***0.20***	***0.07***				
Italy	3.09	2.71	2.80	3.33	3.07	3.10	4.72	5.22	5.29			
diff. from UK	***2.15***	***1.77***		***2.31***	***2.10***		***3.80***	***4.30***				
Latvia												
Lithuania								0.90	0.42			
diff. from UK								***0.02***				
Malta				7.18	4.30	9.07						
diff. from UK				***6.16***	***3.33***							
Netherlands				1.33	1.35	1.31	1.45	1.30	1.14			
diff. from UK				***0.31***	***0.38***		***0.53***	***0.38***				
Poland				0.39	0.18	0.19	0.40	0.19	0.12			
diff. from UK				***0.63***	***0.79***		***0.52***	***0.73***				
Portugal	3.78	7.14	1.83	3.07	2.78	1.89	1.92	1.74	1.61	0.83	1.12	1.04
diff. from UK	***2.84***	***6.20***		***2.05***	***1.81***		***1.00***	***0.82***		***0.15***	***0.38***	
Romania												
Slovenia			0.56			2.06						
Spain												
Sweden	0.82	0.76	1.49	0.58	0.39	0.34	0.59	0.58	0.57			
diff. from UK	***0.12***	***0.18***		***0.44***	***0.58***		***0.33***	***0.34***				
United Kingdom (UK)	0.94	0.94		1.02	0.97		0.92	0.92		0.68	0.74	

Table B.3. Fuel efficiency figures for dredgers compiled from European Scientific Fishery Data (after EC, 2013b). Fuel efficiency is expressed in litres of fuel (L) used per kilogram (kg) of catch landed.

Country	**< 12 m**			**12 - 24 m**			**24 - 40 m**		
	2008	**2009**	**2010**	**2008**	**2009**	**2010**	**2008**	**2009**	**2010**
Belgium								0.77	0.80
diff. from UK								***0.22***	
Bulgaria									
Cyprus									
Denmark	0.04	0.03	0.05	0.02	0.02	0.02			
diff. from UK	***0.47***	***0.68***		***0.43***	***0.46***				
Estonia									
Finland									
France	0.37	0.32	0.32	3.85	0.66	0.72			
diff. from UK	***0.14***	***0.39***		***3.40***	***0.18***				
Germany									
Greece									
Ireland		68.19	19.11						
diff. from UK		***67.48***							
Italy				0.66	0.71	0.66			
diff. from UK				***0.21***	***0.23***				
Latvia									
Lithuania									
Malta									
Netherlands									
Poland									
Portugal	0.90	1.43	1.65	1.00	0.97	1.31			
diff. from UK	***0.39***	***0.72***		***0.55***	***0.49***				
Romania									
Slovenia									
Spain									
Sweden									
United Kingdom (UK)	0.51	0.71		0.45	0.48		0.74	0.55	

Table B.4. Fuel efficiency figures for drift and/or fixed netters compiled from European Scientific Fishery Data (after EC, 2013b). Fuel efficiency is expressed in litres of fuel (L) used per kilogram (kg) of catch landed.

Country	**< 12 m**			**12 - 24 m**			**24 - 40 m**		
	2008	**2009**	**2010**	**2008**	**2009**	**2010**	**2008**	**2009**	**2010**
Belgium					1.24	0.63			
diff. from UK					***0.68***				
Bulgaria									
Cyprus									
Denmark									
Estonia									
Finland									
France	1.07	0.74	0.89	0.78	0.92	0.80			
diff. from UK	***0.47***	***0.22***		***0.18***	***0.36***				
Germany				0.15	0.08	0.09	1.25	1.91	0.82
diff. from UK				***0.45***	***0.48***		***0.90***	***1.45***	
Greece									
Ireland				9.53	9.32	4.12			
diff. from UK				***8.93***	***8.76***				
Italy									
Latvia							0.79	0.40	0.36
diff. from UK							***0.44***	***0.06***	
Lithuania		0.16	0.16		0.28	0.27			
diff. from UK		***0.36***			***0.28***				
Malta	9.02	46.57	3.34						
diff. from UK	***8.42***	***46.05***							
Netherlands									
Poland				0.39	0.15	0.19			
diff. from UK				***0.21***	***0.41***				
Portugal	1.47	0.99	1.60	1.35	0.88	1.07			
diff. from UK	***0.87***	***0.47***		***0.75***	***0.32***				
Romania									
Slovenia			1.26			3.41			
Spain									
Sweden				0.49	0.31	0.37			
diff. from UK				***0.11***	***0.25***				
United Kingdom (UK)	0.60	0.52		0.60	0.56		0.35	0.46	

Table B.5. Fuel efficiency figures for pelagic trawlers compiled from European Scientific Fishery Data (EC, 2013b). Fuel efficiency is expressed in litres of fuel (L) used per kilogram (kg) of catch landed.

Country	**12 - 24 m**			**24 - 40 m**			**40+ m**		
	2008	**2009**	**2010**	**2008**	**2009**	**2010**	**2008**	**2009**	**2010**
Belgium									
Bulgaria				0.16	0.11	0.08			
Cyprus									
Denmark									
Estonia	0.05	0.04	0.02	0.07	0.07	0.06			
Finland	0.02	0.03	0.02	0.06	0.08	0.08			
France									
Germany									
Greece									
Ireland				0.20	0.21	0.16	0.11	0.10	0.09
Italy	0.50	0.46	0.31	0.59	0.70	0.64			
Latvia	0.16	0.14	0.14	0.07	0.07	0.07			
Lithuania					0.05	0.07		0.43	0.66
Malta									
Netherlands							0.31	0.03	0.02
Poland				0.11	0.07	0.09			
Portugal									
Romania					0.74	1.67			
Slovenia						0.65			
Spain									
Sweden				0.12	0.08	0.11	0.09	0.10	0.11
United Kingdom (UK)									

Table B.6. Fuel efficiency figures for purse seiners compiled from European Scientific Fishery Data (EC, 2013b). Fuel efficiency is expressed in litres of fuel (L) used per kilogram (kg) of catch landed.

Country	**< 12 m**			**12 - 24 m**			**24 - 40 m**		
	2008	**2009**	**2010**	**2008**	**2009**	**2010**	**2008**	**2009**	**2010**
Belgium									
Bulgaria									
Cyprus									
Denmark									
Estonia									
Finland									
France				0.05	0.06	0.07			
Germany									
Greece									
Ireland									
Italy				0.68	0.57	0.44	0.34	0.29	0.27
Latvia									
Lithuania									
Malta									
Netherlands									
Poland									
Portugal	0.17	0.15	0.15	0.12	0.13	0.12	0.13	0.12	0.14
Romania									
Slovenia						0.20			
Spain									
Sweden									
United Kingdom (UK)									

Table B.7. Fuel efficiency figures for vessels using other active gear compiled from European Scientific Fishery Data (EC, 2013b). Fuel efficiency is expressed in litres of fuel (L) used per kilogram (kg) of catch landed.

Country	< 12 m			12 - 24 m		
	2008	2009	2010	2008	2009	2010
Belgium						
Bulgaria						
Cyprus						
Denmark						
Estonia						
Finland						
France		3.65	2.45			
Germany						
Greece						
Ireland						
Italy						
Latvia						
Lithuania						
Malta	0.14	2.38	1.87	2.00	0.79	0.97
Netherlands						
Poland						
Portugal						
Romania						
Slovenia						
Spain						
Sweden						
United Kingdom (UK)						

Table B.8. Fuel efficiency figures for vessels using active and passive gear compiled from European Scientific Fishery Data (EC, 2013b). Fuel efficiency is expressed in litres of fuel (L) used per kilogram (kg) of catch landed.

Country	< 12 m			12 - 24 m			24 - 40 m		
	2008	2009	2010	2008	2009	2010	2008	2009	2010
Belgium									
Bulgaria					0.75	0.26			
Cyprus									
Denmark	0.47	0.61	0.49	0.63	0.56	0.54			
Estonia									
Finland									
France		0.26	0.31						
Germany									
Greece									
Ireland	4.78								
Italy									
Latvia									
Lithuania									
Malta	0.33	2.01	2.01	2.28	0.78				
Netherlands									
Poland									
Portugal	0.84	1.02	0.81	0.73	0.85	0.68	0.78	1.52	0.74
Romania			0.05	0.32			0.19	0.20	
Slovenia			1.02						
Spain									
Sweden									
United Kingdom (UK)									

Table B.9. Fuel efficiency figures for vessels using hooks compiled from European Scientific Fishery Data (after EC, 2013b). Fuel efficiency is expressed in litres of fuel (L) used per kilogram (kg) of catch landed.

Country	< 12 m			12 - 24 m			24 - 40 m		
	2008	2009	2010	2008	2009	2010	2008	2009	2010
Belgium									
Bulgaria									
Cyprus									
Denmark									
Estonia									
Finland									
France	1.40	1.11	1.01						
diff. from UK	***0.81***	***0.34***							
Germany									
Greece									
Ireland									
Italy				2.15	1.95	1.67			
diff. from UK									
Latvia									
Lithuania									
Malta	3.81	4.13	2.64	1.73	2.32	2.55			
diff. from UK	***3.22***	***3.36***							
Netherlands									
Poland					1.00	0.65			
Portugal	0.63	0.88	1.79	0.67	0.88	0.78	0.88		1.12
diff. from UK	***0.04***	***0.11***					***0.05***		
Romania									
Slovenia			7.23						
Spain									
Sweden									
United Kingdom (UK)	0.59	0.77					0.83	0.89	

Table B.10. Fuel efficiency figures for vessels using other passive gear compiled from European Scientific Fishery Data (EC, 2013b). Fuel efficiency is expressed in litres of fuel (L) used per kilogram (kg) of catch landed.

Country	**< 12 m**		
	2008	**2009**	**2010**
Belgium			
Bulgaria			
Cyprus			
Denmark			
Estonia			
Finland			
France		0.75	0.19
Germany			
Greece			
Ireland			
Italy			
Latvia			
Lithuania			
Malta			
Netherlands			
Poland			
Portugal			
Romania			
Slovenia			
Spain			
Sweden			
United Kingdom (UK)			

Table B.11. Fuel efficiency figures for vessels using passive gears only compiled from European Scientific Fishery Data (EC, 2013b). Fuel efficiency is expressed in litres of fuel (L) used per kilogram (kg) of catch landed.

Country	**< 12 m**			**12 - 24 m**		
	2008	**2009**	**2010**	**2008**	**2009**	**2010**
Belgium						
Bulgaria						
Cyprus						
Denmark						
Estonia						
Finland						
France		1.14	0.71		1.00	1.05
Germany						
Greece						
Ireland						
Italy						
Latvia						
Lithuania						
Malta						
Netherlands						
Poland						
Portugal						
Romania						
Slovenia						
Spain						
Sweden						
United Kingdom (UK)						

Table B.12. Fuel efficiency figures for vessels using polyvalent passive gears only compiled from European Scientific Fishery Data (EC, 2013b). Fuel efficiency is expressed in litres of fuel (L) used per kilogram (kg) of catch landed.

Country	**< 12 m**			**12 - 24 m**		
	2008	**2009**	**2010**	**2008**	**2009**	**2010**
Belgium						
Bulgaria						
Cyprus				1.10	2.48	1.32
Denmark	0.23	0.23	0.24	0.17	0.27	0.17
Estonia						
Finland						
France		0.62	0.66			
Germany						
Greece						
Ireland						
Italy	1.73	1.66	1.75	1.54	1.46	1.85
Latvia	0.04	0.02	0.02			
Lithuania						
Malta	11.95		2.10			
Netherlands						
Poland						
Portugal	1.00	1.84	1.06			
Romania						
Slovenia						
Spain						
Sweden						
United Kingdom						

Table B.13. Fuel efficiency figures for vessels using pots and/or traps compiled from European Scientific Fishery Data (after EC, 2013b). Fuel efficiency is expressed in litres of fuel (L) used per kilogram (kg) of catch landed.

Country	**< 12 m**			**12 - 24 m**		
	2008	**2009**	**2010**	**2008**	**2009**	**2010**
Belgium						
Bulgaria						
Cyprus						
Denmark						
Estonia						
Finland						
France	0.44	0.49	0.50	0.21	0.56	0.50
diff. from UK	***0.20***	***0.29***		***0.66***	***0.03***	
Germany						
Greece						
Ireland	2.13	2.73	1.61	2.57	1.38	0.43
diff. from UK	***1.49***	***1.95***		***1.70***	***0.79***	
Italy						
Latvia						
Lithuania						
Malta						
Netherlands						
Poland						
Portugal	0.60	0.36	1.05	0.99	1.23	0.88
diff. from UK	***0.04***	***0.42***		***0.12***	***0.64***	
Romania						
Slovenia			2.67			22.65
Spain						
Sweden						
United Kingdom	0.64	0.78		0.87	0.59	

Table B.14. Mean difference between the UK and other country fishing fleet fuel efficiency figures across all gear types, active gear types and passive gear types. Created using difference figures from Tables B.1 to B.13.

Country	Mean difference from the UK			Ranked similarity to UK		
	All gear	Active gear[a]	Passive gear[b]	All gear	Active gear[a]	Passive gear[b]
Belgium	0.70	0.70	0.68	7	8	7
Bulgaria						
Cyprus						
Denmark	0.70	0.70		8	7	
Estonia						
Finland						
France	0.50	0.64	0.36	4	3	6
Germany	0.71	0.67	0.82	9	4	8
Greece						
Ireland	7.57	10.68	3.94	12	12	9
Italy	1.89	1.89		11	10	
Latvia	0.25		0.25	2		2
Lithuania	0.22	0.02	0.32	1	1	4
Malta	11.76	4.75	15.26	13	11	10
Netherlands	0.68	0.68		6	6	
Poland	0.55	0.67	0.31	5	5	3
Portugal	0.92	1.45	0.35	10	9	5
Romania						
Slovenia						
Spain						
Sweden	0.29	0.33	0.18	3	2	1

a) Beam trawlers, demersal trawlers and/or seiners, dredgers, pelagic trawlers, vessels using other active gears, vessels using active and passive gear, vessels using polyvalent active gears only.

b) Drift/fixed netters, purse seiners, vessels using hooks, vessels using other passive gears, vessels using passive gears only, vessels using polyvalent passive gears only, vessels using pots and/or traps.

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