1 AIS bottom-up estimation methodology

1.1 Ugé, Scheidweiler, and Jahn (2020)

1.2 Jalkanen et al. (2009)

- original to use bottom up methodology?

1.3 Olmer et al. (2017)

- basis methodology for Fourth IMO GHG study 2020

1.4 *Faber et al. (2020)

- Main Comparison
- create comparisons of total emissions, missing data, distance travelled
- do similar comparison to MRV validation exercise

1.5 Ventikos et al. (2021)

- basic predictive tool for emissions based on bottom-up methodology

1.6 Moreno-Gutiérrez et al. (2019)

- Comparison of different bottom-up methodologies, including IMO, jalkanen, EPA, etc.

1.7 Johansson, Jukka-Pekka Jalkanen, and Kukkonen (2017)

- method for the collection and processing of the technical ship data, using data assimilation techniques
- use for comparison of emissions estimates
- inclusion of the route generation algorithm

1.8 Tvete et al. (2020)

- VERDE model

2 AIS bottom-up compared to MRV

2.1 *Faber et al. (2020)

- Uses 2018 MRV to validate bottom-up approach
- -0.5% discrepancy on CO_2 emissions

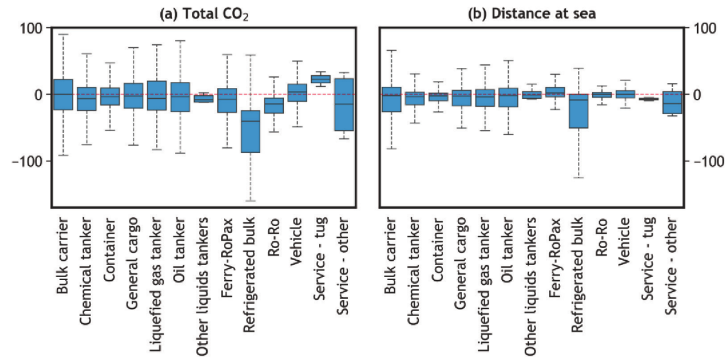
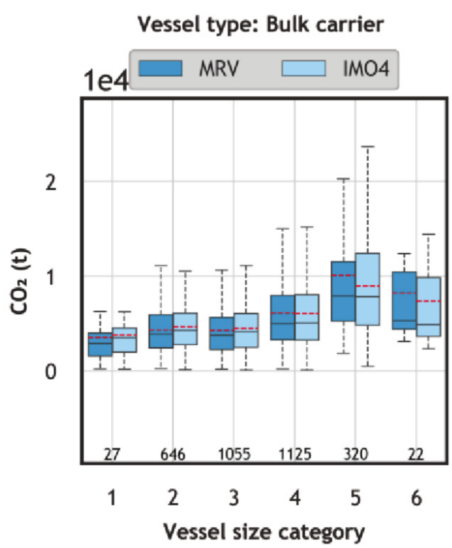


Figure 104 – *Variability in error in (a) total CO_2 and (b) distance at sea agreement between this study's estimates and MRV data 2018*

- sample includes data for over 11,000 vessels which, following basic filtering for the purposes of this study (Hours at sea $\in [0, 8760]$, EEOI $\in [0, 1000]$), was reduced to 9,739 vessels (81.4% of the original MRV dataset). This accounts for around 10% of the world's fleet or more than 30% of the world's fleet over 5000 gross tonnage...The reduction in dataset size is not a reflection of the MRV data quality but stems from the retention of the metrics of interest (e.g. transport expressed in t.nm)
- discrepancy for bulkers by size category



- **A detailed comparison of distance sailed at sea and sailing hours obtained from the matched MRV and bottom-up datasets is presented in Appendix P. (page 453)**

- Distance sailed is systematically higher than reported in MRV, likely due to discrepancy in definition of 'sailing' status between IMO and MRV
- temporal and distance carbon intensity are both consistently lower than reported in MRV (distance one is less consistent for other ship types like tankers)
- they attribute lower AER to overestimating cargo
- Representativeness of fleet reporting MRV:
  - "operation and fleet coverage were highly representative of global equivalents"
  - compared operating speeds of ships when on EU trips vs other trips
  - proportion of year spent in EU routes

2.2 *Marine Benchmark Research Brief

- They underestimate bulkers by about 3% (in terms of kg/nm - I think just comparing reported EEDI)

2.3 Doundoulakis and Papaefthimiou (2022)

- for 5 ferries in Crete in 2020
- 6–12% difference bottom-up vs MRV (MRV lower)

2.4 Mannarini, Carelli, and Salhi (2020)

- Ro-Pax
- clustering of efficiency on certain variables you would expect
- copernicus wave height
- probably not pertinent

2.5 Hensel, Ugé, and Jahn (2020)

- compares MRV to calcs for tiny sample
- modelling efficiency from MRV

2.6 S. Wu et al. (2023)

- ship technical details,AIS trajectory, and weather
- MRV used as quasi-ground truth
- compare different modelling techniques for estimating emissions:
  - Baseline: $load * distance * 3$
  - Gross-tonnage: GT, operational hours, and piece-wise function of operating mode
  - Speed-cubic: $power * (speed/S)^3 * time * emission\ factor$
  - IMO: what we did
  - STEAM: includes weather with penalty term based on waves inside cubic term
- waves seem to have small effect on total emissions (2% increase in emissions)
- *Equation for cargo load using DWT and draught!
- the three speed-based models return similar results
- Emission results from the three speed-based models are consistent with the MRV dataset
- just uses EEDI from MRV to calculate emissions!

3 Validity of MRV

3.1 Panagakos et al. (2019)

- tiny sample size, result is mostly due to the obvious fact that the measures don't account for speed, draft, etc.
- geographic coverage restrictions of the MRV Regulation introduce a significant bias, thus prohibiting their intended use (questionable, small sample - also doesn't account for speeds)
- information was collected on all voyages performed within 2018 by a fleet of 1041 dry bulk carriers operated by a leading Danish shipping company
- the point that the MRV efficiency measure (EEOI) is not very informative is probably valid

3.2 Rony et al. (2019)

- brings up issue of intentionally misreporting to maintain ship's undeclared stock (no more details though!)
- Daily fuel consumption of different types of machinery on board ships is transmitted to the head office via relevant electronic forms.
- 29% (n = 21) of the participants pointed towards intentional misreporting, including 11% (n = 8) citing intentionally maintaining ship's undeclared stock and 18% (n = 13) citing fraudulent entry of data

3.3 Rony (2017)

- more detail on previous survey

3.4 Fridell, Sköld, and Bäckström (2018)

- Sources of measurement error in MRV reports
- MRV allows four monitoring methods:
  - bunker delivery notes: BDNs have an accuracy level of 1 to 5%
  - bunker fuel tank monitoring on-board: electronic, mechanical, manual (most common) - accuracy of tank monitoring is estimated at 2-5%
  - flow meters for applicable combustion processes: accuracy better than 3%
  - direct emission measurements (very uncommon): CO2 stack emissions can be monitored to an accuracy of +/-2%

3.5 P. Chen, Zheng, and B. Wu (2022)

- Reviews emissions tracking methods (e.g. fuel vs direct measurement), similar information to Fridell et al (2018)

4 Effect of COVID on shipping emissions

4.1 Marine Benchmark Research Brief

- Around 4% reduction year on year from only vessels with AIS across all types of ships

4.2 Xu et al. (2023)

- some GARCH model thingy

4.3 Ju and Hargreaves (2021)

- Western Singapore Straits

4.4 Mujal-Colilles et al. (2022)

- Port of Barcelona

4.5 Q. Chen et al. (2023)

- Danish waters

4.6 Durán-Grados et al. (2020)

- Strait of Gibraltar

4.7 *Millefiori et al. (2021)

- AIS data to quantify mobility change from COVID
- between +2.28 and -3.32% for dry bulk during March-June 2020
- our analysis of AIS data shows that in all highlighted areas, on average, ships reduced their speed in March–April 2020 with respect to the same months in 2019
- Specifically, in the highlighted regions of the Gibraltar-Suez route, Ligurian Sea, Northern Adriatic Sea, and Aegean Sea, we report average fleet speed variations of -5.1%, -15.3%, -6.0% and -9.5%, respectively.
- indicators are the (monthly) Cumulative Navigated Miles (CNM), computed for each ship journey per category, the number of active and idle (status as idle or speed below 2kts) ships and their average speed (no details)

4.8 Deng and Mi (2023)

- not very pertinent
- general review on bottom-up and top-down methods
- only IEA (aggregate fuel consumption-based) method and EDGAR (not specific to shipping) for COVID period

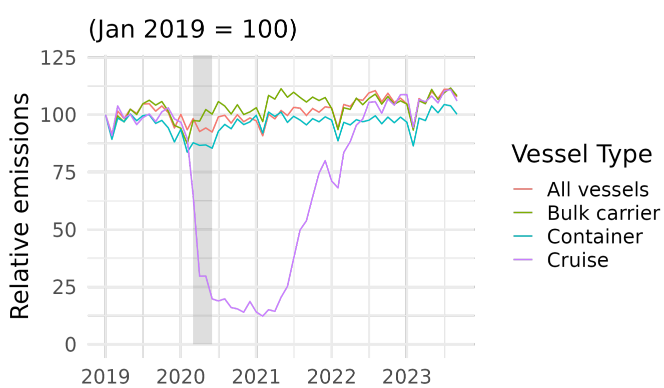
4.9 Mou et al. (2024)

- not particularly pertinent
- spatiotemporal changes of ship emissions in U.S. EEZ
- covers covid years

5 AI/ML and Shipping Emissions

5.1 *Clarke et al. (2023)

- predict an emissions efficiency ratio for each ship
- random forest
- emissions efficiency ratio is then multiplied by the distance travelled by the ship to obtain its CO2 emissions.
- Contributions: country coverage (vs AEA), frequency (monthly, updated quarterly), accuracy (bottom-up from AIS)
- we take the variable average CO2 emissions per nautical mile from this dataset as the target variable to train the regression model
- activity-based approach include Goldsworthy et al. (2015[8]), Olesen et al. (2010[13]), Jalkanen et al. (2017[14]), Coello et al. (2015[15]), Ng et al. (2013[16]), Chen et al. (2016[4]), Johansson et al. (2017[14]), Leong et al. (2015[5])
- Another common approach is a top-down approach using bunker fuel sales or consumption to estimate ship emissions. This approach has been studied by Olivier et al. (1999[17]), Endresen et al. (2003[18]), and Mao et al. (2022[19]), among others
- bottom-up approach that differs from the traditional activity-based bottom-up approach outlined above (Equation 1) in that it exploits vessel-level information, as the traditional method does, but simplifies the modelling of ship specification and movement
- This approach builds on a similar strategy used by team Blue Carbon from the Wärtsilä Corporation25 in the 2020 UN Hackathon for AIS data.
- data published by on OECD website
- Does not account for cubic relationship of fuel consumption with speed (important because of potential effects of recent regulations!)
- COVID effect:

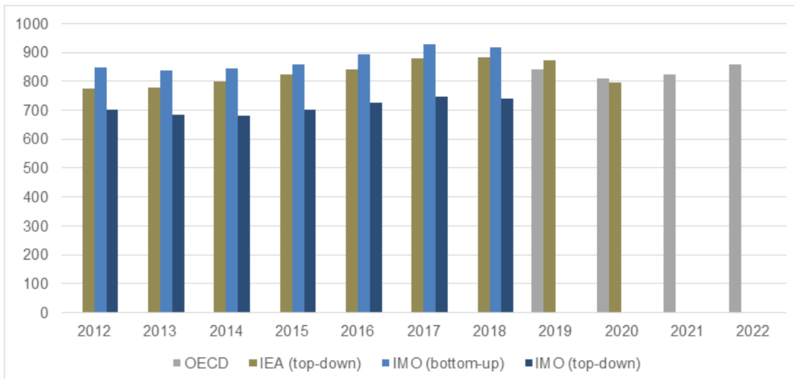


- The assumptions underpinning this approach are that the technical specifications of a vessel stay constant in the short term, that differences in emissions efficiency during a voyage average out, and that changes in a ship's emissions come principally from the amount of distance covered in a given time period.

- Comparison with other methods:

Figure 5.1. Annual estimates for the global fleet compared

Million tonnes of CO_2



Notes: IEA estimates (top-down) are based on all fuel consumed by shipping: both domestic and international. The IMO top-down estimate is voyage-based and covers all international shipping excluding fishing. The IMO bottom-up estimate is vessel-based and uses AIS data.
Sources: OECD database, IEA Detailed CO2 Estimates, (IMO, 2020[1]).

5.2 Ren et al. (2022)

- daily MRV reports from COSCO
- containerships
- wind and wave categories (clustering)
- ridge vs ANN
- very small sample of ships

5.3 Shaohan Wang et al. (2023)

- Neural Network
- Include weather
- For example, Du et al. [32] employed an artificial neural network (ANN) with voyage report data's speed to predict fuel consumption and test future voyage report accuracy. Petersen J.P. et al. [23] compared the performance of ANN and Gaussian Process (GP) in estimating a ship's propulsion efficiency. Farag YBA et al. combined ANN with polynomial regression to estimate a ship's power and fuel consumption, enabling it to operate in real-time environments and adapt to changes in the ship's environment

- "Existing studies, including the GBMs, only tries to insert physical-based equations inside the DL models which can result in a very time consuming process."
- China COSCO Shipping Corporation Limited provided MRV data for vessels from 2020-8-1 to the present. Measurement, reporting, and verification (MRV) record the total fuel consumption consumed by each vessel for each daily route and job.
- 11 ships: 5 container, 3 bulk, 3 tankers
- theoretical sailing speed: $speed = screw\ pitch * engine\ speed * 60/18520000$
- ANN, ridge regression and polynomial regression
- Only 8 RHS variables, 3 weather, 3 loading, engine speed, speed, distance
- training, test, validation, not cross-validation

5.4 Guo et al. (2022)

- According to Yin et al. (2017), 15 of 32 papers, which adopt a bottom-up approach, apply the 'Cubic Rule' as one of the basic assumptions for main engine load factors estimation.
- The power three relationship is a simplification, and it is not accurate for most ships - references Adlan 2020
- ML technology is introduced to extend the application of the VERDE model to a large fleet of ships, and to increase the computational speed and reduce the computational cost at the same time
- ML to calculate the added resistance due to weather, and to impute the missing propeller diameter is described in this section.
- Uses AIS tracking and NOAA weather data
- Tvete et al. (2020) develop a VERDE model
- added resistance due to wind: one is based on the formula given by Fujiwara et al. (2005, 2006) and another is based on Blendermann's method (1994). The added resistance due to head wave is calculated using the method given by Liu and Papanikolaou (2016), and the effect of the wave direction is modelled with a simple penalty function, given by Jalkanen et al. (2009).
- uses IHS Fairplay Ship database
- EIAPP database contains SFOC curve information for different engine types and sizes
- Holtrop/Mennen empirical method is used to calculate the calm water resistance: additive formula of resistance components
- maximum added resistance due to fouling is about 10% of the calm water resistance
- Added resistance due to waves

- Added resistance due to wind
- various others: hull efficiency, propeller efficiency, rotative efficiency and shaft efficiency...
- uses calculated wave resistance to train??
- predict missing propeller diameter data based on length, etc.

5.5 Fletcher et al. (2018)

- No access
- develop a shipping emission inventory model incorporating Machine Learning tools to estimate gaseous emissions

5.6 Ay, Seyhan, and Beşikçi (2022)

- Basic forward prediction of emissions
- limited to Istanbul Strait

5.7 Hu et al. (2019)

- Ship-level prediction of fuel consumption using neural net, real-time consumption data from a containership, weather data

5.8 Yan et al. (2023)

- analyzes and compares MRV records in 2018 and 2019, and then develops machine learning models for annual average fuel consumption prediction for each ship type combining ship features from an external database
- mean absolute percentage error (MAPE) on the test set no more than 12% and the average R-squared of all the models at 0.78
- "first fuel consumption prediction models from a macro perspective using the MRV data"
- one regression model for each ship type with more than 500 valid records
- use the calculated annual average sailing speed from the MRV system as an input
- World Register of Ships (WRS)
- prediction target: annual average fuel consumption per distance (kg/nm)
- gradient boosting regression tree, one for each ship type
- impurity-based feature importance - directly from GBRT

5.9 Jebsen and Mathiesen (2020)

- operational data from 16 oil tankers from a single anonymous international shipping company
- 14,098 noon reports with variables such as: report date; vessel name; departure and destination ports; longitude and latitude; draft in metres; two measures of average daily speed in knots (speed over water (GPS-speed) and speed through water (LOG-speed)); fuel consumption in metric tons per day; daily distance in nautical miles; whether the vessel is ballast or laden; relative wind and swell direction and wind type; sea state and swell state
- Copernicus database for wind and calculate trim (difference between forward and aft draft)
- "ensemble method" with stacking, weighting based on each method's performance
- p53 variable importance

5.10 Monisha, Mehtaj, and Awal (2023)

- ML on noon day reporting bangladesh

5.11 Yang et al. (2024)

- ML for improving raw AIS data?

6 Nowcasting

6.1 Pandis Iveroth et al. (2022)

- Scandinavian, across all sectors

6.2 Arslanalp, Marini, and Tumbarello (2019)

6.3 Cerdeiro et al. (2020)

7 Hybrid Physical/Engineering Theory + ML Ensemble Prediction, i.e. Residual Prediction

- Anything?

8 Unclassified

8.1 Loeff, Godar, and Prakash (2018)

- commodity-specific emissions using Brazilian bills of lading

8.2 Castells-Sanabra and Borén (2020)

- not pertinent, discusses methods of implementing MRV

8.3 Lundkvist (2023)

- student project
- does reporting reduce emissions?

8.4 Luo, Yan, and Shuaian Wang (2023)

- explores MRV data with graphs

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