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An analysis of an AMSA ship survey and comparison with the Maritime Transport Emission Model (MTEM)

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ABSTRACT

This study analyses the results from an Australian ship survey and evaluates the performance of the Maritime Transport Emission Model (MTEM) that uses detailed data on local ship movement (Automatic Identification System) and ship characteristics. The model is designed to make accurate predictions at fleet level. The survey collected comprehensive information for 172 vessels in 2019, mainly bulk carriers, which dominate the Australian fleet. At fleet level and using default model settings, fuel consumption in transit and stationary (at berth) operating conditions are predicted with an error of 12% and 6%, respectively. For individual vessels, model predictions are significantly less reliable, which confirms that MTEM should be used for its intended purpose and estimate emissions at fleet level in regional areas. In transit conditions, the 95% confidence interval for fuel use prediction errors lies between about −50% and +75%. In stationary conditions, at berth, prediction errors can be larger, but the results suggest that these errors cancel each other out at fleet level, resulting in satisfactory overall model performance. Reported sulphur content in marine fuels confirms that the default emission factor for sulphur dioxide is still a reasonable estimate.

1. Introduction

International shipping is critical for global trade. IMO (2018) reports that more than 80% of the volume of international trade in goods is transported by sea by over 90,000 commercial ships with a combined weight of 1.86 billion dead weight tonnes.

Shipping is a significant source of air pollution and greenhouse gas emissions. Ocean-going Vessels (OGVs) have long service lives and generally use large diesel engines that run on heavy bunker fuels, traditionally without emission controls. Annually, international shipping is responsible for approximately 13% and 12% of global nitrogen oxides (NO_x) and sulphur oxides (SO_x) emissions respectively (IMO, 2018). Several studies have reported substantial effects on local air quality in and around port areas (e.g. Saxe and Larsen, T., 2004; Agrawal et al., 2009; EEA, 2013; Viana et al., 2014; Broome et al., 2016; Monteiro et al., 2018; Smit and Khan, 2019; Contini and Merico, 2021). Greenhouse gas emissions from the shipping industry have become increasingly important (Cullinane and Cullinane, 2013). According to IMO (2018), maritime transport emits around 1 billion tonnes of carbon dioxide annually and is responsible for approximately 3% of global greenhouse gas emissions from fuel combustion. Shipping is forecast to grow as international trade grows. The shipping sector is expected to increase its CO_2 emission contribution from 3% in 2007 to 18% in 2050 if no action is taken (IEA Bioenergy, 2017).

To assess the impacts of shipping on greenhouse gas emissions and local air quality, an Australian ship (exhaust) emission model (Maritime Transport Emission Model, MTEM) was initially developed in 2019 (DES, 2019). It uses detailed data on local ship movements, high-resolution terrestrial or satellite Automatic Identification System (AIS) data and information regarding relevant ship characteristics. MTEM estimates fuel use and subsequently uses fuel-based emission factors (g/kg fuel) to estimate air pollutant and greenhouse gas emissions. The model is based on extensive literature review and model parameters were calibrated for the Australian fleet using an energy balance approach (Smit and Khan, 2019), as will be discussed later. A comparison with other ship emission models is provided in Section 2.3.

There are various ways to measure real-world ship emissions and validate a ship emissions model, including on-board emissions testing, laboratory engine test beds and mobile or stationary plume measurements (e.g. Jayaram et al., 2011; Lack et al., 2011; Westerlund et al. 2015, Chu-Van et al., 2018; Grigoriadis et al., 2021). The US EPA (2022) states that vessel surveys can also provide useful data for estimating emissions. In this study, we have analysed the results from a vessel survey conducted by the Australian Maritime Safety Authority (AMSA)

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with the aim to assess MTEM performance. Another study has examined the performance of the same model but by using a different method; on-board emissions testing (Smit et al., 2022).

2. Method

2.1. AMSA vessel survey

The Australian Maritime Safety Authority (AMSA) conducted a voluntary survey to collect operational data relevant for ship emissions in Australian waters. The full survey is included in the Supplementary Material (SM1). The survey consisted of 42 detailed questions and data were provided for 172 vessels for the period January 2019 to July 2019. The survey was promulgated via the AMSA website and by AMSA surveyors during ship inspections and targeted all ships types and all Australian ports. The survey was also promoted by the peak maritime industry bodies – Maritime Industry Australia Limited (MIAL) and Shipping Australia Limited (SAL).

Ships masters were given a survey to complete in their own time. Ships could fill the survey in via SurveyMonkey or hard-copies and return to the AMSA surveyor or via email. The completed surveys were reflective of the variety of different ship types that visit or operate in Australian waters. Bulk carriers are the dominant ship type arriving in Australian ports and the majority of surveys were completed by ships arriving at bulk commodity ports, such as Port Hedland, Newcastle and Hay Point.

The survey data were complemented with detailed ship information. This ship information was used to verify survey data and to plug data gaps. In addition, the survey data were extensively checked for consistency and typos were rectified. Unrealistic data entries were removed and marked as missing values. For main engine fuel use in transit conditions, 12 surveyed vessels reported unrealistically high fuel use (>200 tonne/day) at rated engine power <20 MW. One vessel with a rated engine power of 40 MW reported an unrealistically low fuel use (32 tonne/day). Of the 172 vessels in the survey, these 13 vessels (8%) were identified as having invalid data entries and were removed, as will be discussed later. For self-reported fuel use at berth, one vessel reported an unrealistic 800 tonne/day in the survey and was removed.

2.2. Maritime transport emission model (MTEM)

MTEM is an energy-based ship (exhaust) emissions model. Full A detailed discussion of the model foundations can be found in DES (2019) and Smit and Khan (2019). Table 1 presents the general structure of the fuel consumption algorithms used in the ship emission model for moving ships and stationary ships. It is noted that separate algorithms are used for auxiliary engines in manoeuvring conditions, which are defined as <20% Maximum Continuous Rating (MCR). They are not shown in Table 1 as the survey did not collect sufficient information related to manoeuvring conditions. The calibrated model parameters by ship type are included in the Supplementary Material (SM2).

Table 1
General structure of fleet-average fuel consumption prediction algorithms in MTEM.

Fuel consumption variable	Algorithm
Main engine (kg)	$\varphi_1 \mathrm{a}\, \mathrm{S}^{\mathrm{b}}\, \Delta \mathrm{d}\, p_i\, (\nu/\nu_{ss})^3$
Auxiliary engine in transit conditions (kg)	$\varphi_1 \varphi_2 \mathrm{a}\, \mathrm{S}^{\mathrm{b}}\, \Delta \mathrm{d}\, p_i$
Auxiliary engine in stationary conditions (kg)	$(\psi\, \mathrm{d}\, \mathrm{S}\Delta \mathrm{t} - \mathrm{fb})\, p_i$ with $\psi = {}_{\mathrm{e}}\, (\tau\, \eta\, \mathrm{d}\, \mathrm{S}\, \Delta \mathrm{t})^{\mathrm{f}-1}$
Auxiliary boiler (kg)	$(\varphi_3 3.6\, \mathrm{cS}\Delta \mathrm{t})\, /(\tau\, \eta)$

S = vessel size or volume, expressed as gross tonnage (GT); Δd = total distance traversed by the ship (km); Δt = time resolution (h); ν = actual (average) vessel speed (km/h); ν_{ss} = vessel service speed (km/h); η = boiler thermal efficiency, ratio (−); τ = fuel specific lower heating value (MJ/kg); a = model parameter – function of ship class (kg/km); b = model parameter – function of ship class (−); c = model parameter – function of ship class (kW/GT); d = model parameter – function of ship class (kg/GT.h); e = model parameter (1/MJ); f = model parameter (−); φ_1 = main engine calibration factor (−); φ_2 = auxiliary engine calibration factor (−); φ_3 = boiler calibration factor (−); p_i = proportion of total fuel used by machinery/fuel type I (−); ψ = calibration function (−); fb = auxiliary boiler fuel consumption (kg).

Real-world fuel consumption depends on energy demand. However, energy requirements on-board a ship can vary significantly over time and is therefore challenging to quantify accurately for specific vessels and for different combustion systems on-board. Nevertheless, a reasonable and feasible approach is required for emission estimation in large areas and over longer periods of time (months to years). MTEM is based on generic empirical relationships published in previous research (Georgakaki et al., 2005; Hulskotte and Denier van der Gon, 2010). These functions were expanded and then re-calibrated using an energy-balance approach, as will be discussed shortly.

The use of generic functions for shipping fleets in regional areas and substantial periods of time (e.g. one to several years) allows for fast and cost-effective estimation of ship emissions without the need to consider individual ship characteristics. Collection and processing of individual ship information can be a costly and time-consuming part of a ship emissions inventory. The approach is warranted as prediction errors for individual vessels tend to offset each other and average out, leading to robust and reliable emission predictions at fleet level.

However, to better reflect local fleet composition, a ship energy-balance approach was developed to calibrate the model parameters of the empirical functions (Table 1). This is an optional feature of MTEM and it was, for instance, used to properly reflect the Ocean-going vessel fleet operating in Australian waters (DES, 2019; Smit and Khan, 2019). AIS data were analysed to identify which specific vessels (IMO/MMSI numbers) were operating in the area. Plausible ranges in ship energy use and verification points in the energy balance were defined through literature review and analysis of a database with vessel specific information. This included consideration of, for instance, MCR values, service speeds, ratios of installed auxiliary engine power to MCR and engine load factors by type of engine.

A representative and service speed adjustable speed-time profile, including all modes of operation (cruising, manoeuvring, berth, anchor), was used in a simulation to estimate minute-by-minute fuel use for over 5000 vessels. Simulated fuel use was subsequently converted to energy use (kW) for each type of combustion system (main engine, auxiliary engines, auxiliary boilers) using information on fuel type, fuel-specific lower heating values and engine and fuel type dependent thermal efficiency values. A robust linear regression model (RLM), which is less sensitive to outliers than conventional linear regression, was fitted to the simulated energy use for all vessels of a particular type. This fitted regression function was then used to re-calibrate function parameters for each type of ship and achieve an optimum fit to the fleet average verification points with a minimum overall prediction error. The parameter calibration process can be repeated for other regional or local areas.

Typical fuel consumption rates are predicted for different ship classes and for four modes of operation: 'transit', 'manoeuvring', 'berth' and 'anchor'. The main OGV types considered in the model are: 'bulk carrier', 'container', 'cruise ship', 'general cargo', 'reefer', 'roro' (roll-on-roll-off), 'tanker (oil)', 'tanker (other)', 'vehicle carrier' and 'other'. Ship engine type is defined as: 1) main engine (ME), auxiliary engine (AE) and boiler (BL), 2) slow speed (SS), medium speed (MS) and high speed (HS) diesel engines, or gas/steam turbines (GAS/STM), and 3) International Convention for the Prevention of Pollution from Ships (MARPOL) Annex VI NO_x emission certification limits. The last category relates to year of vessel construction, i.e. 'pre-control' (<2000), 'Tier I' (2000–2010), 'Tier II' (2011+) and 'Tier III' (2016+). Tier III is only relevant for NO_x-emission control areas (ECAs), which do not exist in Australia. More specifically, it applies to the North American ECA and the Baltic/North Sea ECA.

Marine fuel oils are broadly classified as (intermediate) residual fuel oil (RO), marine distillates (MD) and ultra-low sulphur diesel (ULSD). MTEM uses fuel-based emission factors (g of pollutant per kg of fuel burned) for air pollutants and greenhouse gases based on a review and analysis of published research reports and scientific papers (e.g. Agrawal et al., 2008; Moldanová et al., 2010; Coggon et al., 2012; Zhang et al., 2014; Celo et al., 2015; Pongpiachan et al., 2015; Goldsworthy and Goldsworthy, 2015; Grigoriadis et al., 2021). They include CO_2, NO_x, SO_2, PM_{10}, $PM_{2.5}$, VOCs, CH_4, N_2O, Pb, As, Ni, V, Mn, Cd, PAHs (sum), benzo(a)pyrene, 1,3-butadiene, benzene, formaldehyde, toluene, xylenes and ethylbenzene. The emission factor values are a function of engine system (ME, AE, BL), engine type (SS, MS, HS, GAS, STEAM), fuel type (RO, MD, ULSD) and MARPOL Annex VI emission certification limit (NO_x only).

In model application, these emission factors are combined with estimates of fuel consumption for each minute of individual ship activity, which is obtained from AIS data. These AIS data undergo elaborate post-processing and verification to ensure realistic speed-time data are used as input to emissions modelling (Smit et al., 2022). This is carried out for all individual ships that operate in the area of interest in a selected base year, resulting in emission predictions at a high temporal and spatial resolution. Ship emission predictions are then aggregated to estimate total emission loads at grid cell level (for instance 1 × 1 km) for each hour of the year to allow for visual presentation of the data in maps and to create emission input data for atmospheric dispersion and chemistry models.

2.3. Comparison with international ship emission estimation methods

MTEM has several communalities in its approach compared with other international methods. For example, in terms of ship classification engine speed category, fuel type and emission control standard are explicitly modelled (Grigoriadis et al., 2021), but also ship type, engine type and mode of operation (Goldsworthy and Goldsworthy, 2015; EMEP/EEA, 2016, 2021; CARB, 2022).

Although ship emission inventories traditionally used generic information and statistics on ship movements (e.g. Corbett and Koehler, 2003; Endresen et al., 2003), AIS data are now commonly used in the development of emission inventories (e.g. Yau et al., 2012; Jonson et al., 2015; Liu et al., 2016) and regarded as best practise (IMO, 2018; EMEP/EEA, 2021; US EPA, 2022). However, a critical aspect is that AIS data cannot be used directly. The data requires post-processing (data cleaning, imputation, statistical smoothing) to enable proper use in emission inventories and poses its own challenges (Ng et al., 2013; Smit et al., 2022). Emmens et al. (2021) provide a detailed examination of the strengths and weaknesses of AIS data.

In other aspects the approach can be slightly different. For example, MTEM first estimates fuel use (kg/min) as a function of ship operating conditions (engine load, operating mode) and subsequently estimates greenhouse gas and air pollutant emissions using fuel-based emission factors (g/kg fuel). In comparison, Grigoradis *et al.* (2022) used separate emission algorithms for each air pollutant, where emissions are expressed as mass of pollutant per unit of energy produced by the engine. The base emission factors (g/kWh) are constant but vary with engine, fuel and emission control and are modified according to operational engine load. Ship emission inventory methods used in the USA (CARB, 2022; US EPA, 2022) similarly use emission factors expressed as g/kWh and operational engine load is typically estimated by combining (default or propellor/admiralty law derived) load factors with vessel-specific rated engine power. The European Emission Inventory Guidebook (EMEP/EEA, 2016, 2021) offers both options (fuel-based or load-based emission factors) for its most detailed Tier 3 emission inventory method.

MTEM uses fuel-based emission factors that are constant across a range of power settings, except for low power conditions <20% MCR (for instance during manoeuvring) where emission factors increase. On-board emissions testing (Smit et al., 2022) has shown that this approach agrees with observed emissions behaviour in some cases, but not for all ships where the power - emission factor relationship can exhibit a different shape. However, significantly more emissions testing would be required to confirm if the current approach needs to be modified.

In addition to established methods (e.g. EMEP/EEA, 2021; US EPA, 2022) other ship emission models are available. For instance, Jalkanen et al. (2009, 2012, 2014) developed a power-based ship emission models called STEAM and STEAM2 (Ship Traffic Emission Assessment Model). The model uses an internal database with specific technical information for a large number of vessels, which includes ship engine data, fuel mix, abatement techniques, as well as fuel use rates and emission factors. Although, detailed vessel information is used to calibrate MTEM to reflect the regional shipping fleet, MTEM is less complex than STEAM in its application as it uses generic prediction functions for different ship types.

3. Results

3.1. General survey results and vessel characteristics

The survey data were collected in 21 ports across Australia with 11% of surveys conducted in New South Wales (Sydney, Newcastle, Port Kembla), 5% in Victoria (Melbourne, Geelong, Point Wilson), 39% in Queensland (Abbot Point, Dalrymple Bay, Gladstone, Hay Point, Mackay, Townsville), 42% in Western Australia (Dampier, Fremantle, Geraldton, Kwinana, Port Hedland, Port Walcott), 2% in Tasmania (Bell Bay) and 1% in the Northern Territory (Darwin).

Survey vessel characteristics are presented in distribution charts in the Supplementary Material (SM3).

The majority (84%) of surveyed ships classify as bulk carrier (Figure SM 3.1) with smaller proportions between 1% and 3% for other ship types. This reflects the fleet composition in Australian waters. For instance, of the more than 5000 vessels used in the MTEM energy calibration step, about 70% were bulk carriers (SM3).

In terms of vessel size, the distributions of vessel length and gross tonnage (GT) are shown SM3.

The mean and median vessel length of the surveyed vessels is 250 and 254 m, respectively. The mean and median gross tonnage (GT) of the surveyed vessels is 68,152 and 58,356, respectively. The mean and median year of manufacture of the surveyed vessels is both 2011. The distribution by year of manufacture suggests that only 5 vessels qualify as pre-control (3%), the majority is Tier I (53%) and the remainder Tier II/III (44%). The survey requested information on engine NO_x certification and the results show 45% Tier I, 35% Tier II, 4% Tier III and 15% with no answer.

The Maximum Continuous Rating (MCR), which is equivalent to maximum installed (main) engine power, varies between 3900 and 68,590 kW, with a mean and median value of 14,621 and 15,131 kW, respectively (SM3). The main engines that propel ocean-going vessels are primarily powered by slow (SS, 2-stroke, typically GT ≥ 2500 and ≤150 RPM) and medium speed diesel (MS, four-stroke, typically GT < 2500 and 150–1000 RPM) engines that combust residual oil (RO) or marine distillate (MD). Most surveyed ships (94%) have a single slow speed main engine. The remaining 6% have one to six medium speed engines.

The conventional engine configuration is one or more main engine(s) and two or more auxiliary engines, with either direct coupling (no gear) to the propeller for large slow-moving engines, or geared drive with a gearbox between the smaller medium-speed engine and propeller to reduce propeller velocity. Of the surveyed ships, the majority (about 90%) have direct drive main diesel engines and less than 5% have geared drive main diesel engines. Ships with limited space or highly variable operation and power requirements such as large passenger ships typically use diesel-electric systems and less than 10% of surveyed ships fall into this category.

Auxiliary engines are typically used for electric power production when the main engine is shut down and an auxiliary boiler (if present) generates steam. The main engine is generally switched off when ships are at berth or at anchorage, except for diesel-electric ships, where auxiliary power is generated with the main engines. The surveyed ships typically have two to five auxiliary engines installed.

Fig. 1 shows the relationship between rated main engine power (MCR) and total installed auxiliary engine power for bulk carriers. The red dotted line shows a fitted robust linear regression model (RLM), including the 95% confidence interval. RLM is used throughput this paper to fit a trend line to the data and quantify the associated uncertainty (95% confidence interval of the mean). It uses a basic linear function: Y (response variable) = a (offset) + b (slope) X (explanatory variable). The offset and slope of the regression line in Fig. 1 are 1102 ± 178 (kW_{aux}) and 0.08 ± 0.012 (kW_{aux}/kW_{mcr}), respectively, which indicates that total auxiliary engine power is typically about 1100 kW plus 8% of MCR for bulk carriers. However, the reported variability for individual vessels is clear in Fig. 1.

3.2. Operational survey information

Operational survey information is of interest as it is often used directly as input to emission inventory development. Since these operational survey data show significantly skewed distributions, a bootstrap analysis was conducted to estimate the mean and associated standard error and non-symmetric 95 percent confidence intervals (95% CI). The bootstrap re-samples the data with replacement and the estimate is calculated for this new resampled data set. This is repeated many times to form an approximate sampling distribution for the estimate, from which standard errors and confidence intervals can be calculated (James et al., 2017).

Distributions of operational survey data are presented in the Supplementary Material (SM3). The duration of the voyage varies substantially from 1 to 99 days. The (bootstrap) mean voyage duration is 11.5 days (95% CI = 10.2–13.2 days). Time spent at berth reportedly varies from 1 to 284 h with a (bootstrap) mean duration of 33 h (95% CI = 28–39 h). Time spent at anchor reportedly varies from 0 to 1094 h with a (bootstrap) mean duration of 165 h (95% CI = 129–204 h).

3.3. Main engine fuel use in transit conditions

The survey requested information regarding total fuel use by the main engine during the voyage to port, as well as the average main engine load factor and the average speed of travel. The cube of the average speed of travel divided by service speed (propellor law) provides an independent estimate of the engine load factor. Service speed is defined as the speed that a ship is stated to be capable of maintaining at sea in normal weather and at normal service draught. Fig. 2 compares the two estimates of average engine load. Although there is a general linear trend and a moderate level of correlation (r = 0.62), there is substantial variability suggesting a certain level of inconsistency in the survey results. Therefore, both estimates of main engine load are used for comparison of reported (survey) and modelled fuel use.

Multiplication of the average main engine load factor with rated main engine power (MCR) gives an estimate of mean operational engine power during the voyage. This is then compared with reported total fuel usage in the main engine on the voyage to arrival port (SM5) to identify the presence of any invalid data. The charts in SM4 show that twelve vessels reported very high and unrealistic fuel use (>200 tonne day) at engine power <20 MW. These outliers (6%) are considered to be incorrect survey data and have been removed.

Fig. 3 compares reported average fuel use by the main engine with predicted fuel consumption in transit conditions. The black dotted line presents a perfect fit between survey data and model predictions. Four cases are considered for main engines and they reflect the use of either the default fuel mix used in the model or reported fuel mix in the survey, as well as the one of two estimates of average engine load discussed earlier (reported in the survey versus estimated with the propellor law). The case numbers and brief descriptions are shown in Table 2. The default fuel mix reflects a proportional and fleet averaged distribution of fuel use by fuel type (RO, MD, ULSD) and engine type (ME or AE and SS, MS and HS) for a particular ship type (sum = 1), whereas reported fuel mix reflect the fuel type actually used by a particular vessel.

Of the 172 vessels in the survey, 13 vessels (8%) were identified as having invalid data entries and were removed, leaving a sample size of 140 (81%) or 147 vessels (85%) with complete data (transit conditions), depending on the case (Table 2).

Model performance statistics are presented for each case in Table 2 and include the linear Pearson correlation coefficient (r), the coefficient

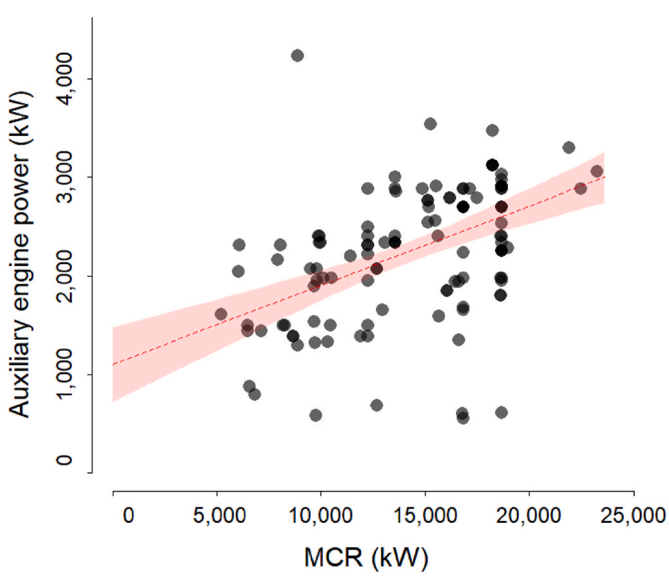

Fig. 1. Relationship between MCR and total installed auxiliary power of surveyed bulk carriers. The chart includes a fitted robust linear regression model (red dotted line) and includes the 95% confidence interval (red semi-transparent polygon).

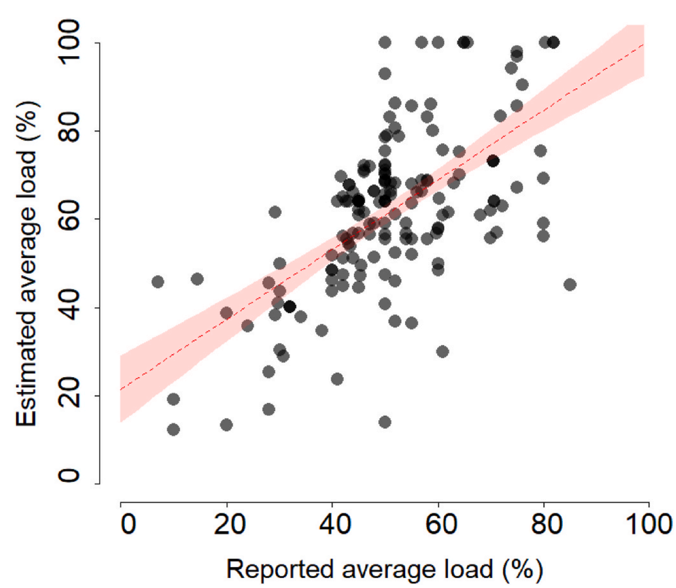

Fig. 2. Correlation between reported and independently estimated main engine load. The chart includes a fitted robust linear regression model (red dotted line) and includes the 95% confidence interval (red semi-transparent polygon).

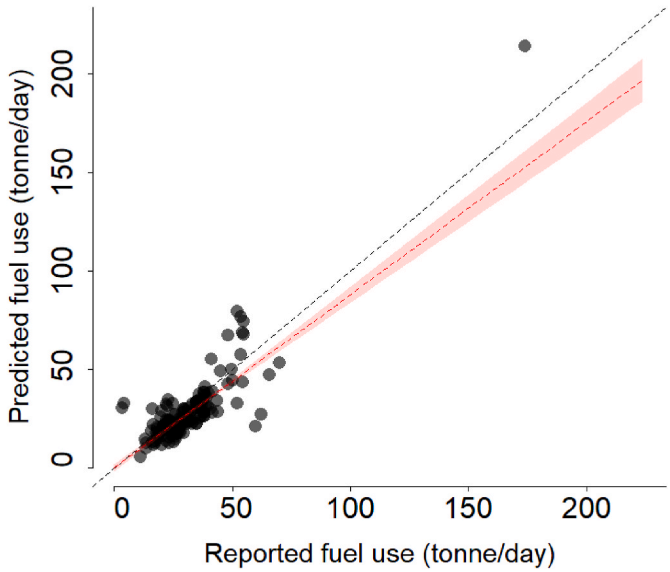

Fig. 3. Predicted versus reported fuel consumption during the voyage to arrival port (Case 1). The chart includes a fitted robust linear regression model (red dotted line) and includes the 95% confidence interval (red semi-transparent polygon).

Table 2
Performance statistics for four cases.

Performance Statistic	Case 1 Reported Fuel Mix and Reported Load	Case 2 Reported Fuel Mix and Estimated Load	Case 3 Default Fuel Mix and Reported Load	Case 4 Default Fuel Mix and Estimated Load
r	0.87	0.84	0.88	0.84
R^2	0.76	0.70	0.77	0.70
RMSE (tonne/day)	10.2	12.6	10.1	12.4
MPE (tonne/day)	0.02	0.23	0.01	0.22
n	140	140	147	147

of determination (R^2), root mean squared error (RMSE), mean prediction error (MPE) and sample size (n).

The use of vessel-specific survey data on fuel mix and mean engine load (case 1) as input to the model predictions leads to reasonable model performance in transit conditions explaining 76% of the variation in the fuel survey data ($R^2 = 0.76$) and a mean prediction error of 0.02 tonne/day. The fitted parameters for the robust linear regression model (Fig. 3) are 0.21 ± 1.17 (intercept ± SE) and 0.88 ± 0.033 (slope ± SE). This suggest that the model offset (intercept) is not statistically significant but that the model tends to underpredict survey data at higher rates of fuel use.

A similar but slightly improved prediction performance is seen when the default fuel mix is used rather than the reported fuel use (Case 3), which suggests that the model is not sensitive to variability in fuel mix. This lack of sensitivity to fuel mix is to some extent explained by the relatively stable specific fuel consumption values used in MTEM for the different combinations of fuel type and engine type. They vary from 181 to 228 g/kWh.

When the default modelling method to engine load prediction (propellor law) is used rather than reported engine load (Case 2), prediction performance is reduced explaining 70% of the variation in the fuel survey data ($R^2 = 0.70$) with a mean prediction error of 0.23 tonne/day. In addition, the fitted robust linear regression model suggests a slight overprediction of fuel consumption in transit (slope = 1.11 ± 0.050), but a statistically insignificant intercept (−0.24 ± 1.805).

Finally, the use of default values in the model for fuel mix and the default method for mean engine load estimation (Case 4) initially led to the lowest model performance, explaining 59% of the variation in the fuel survey data ($R^2 = 0.59$) with a mean prediction error of 0.24 tonne/day. The deterioration in model performance was caused by a single vessel, which reported a fuel consumption of 31.6 tonne/day, whereas the model predicts 150.8 tonne/day. This particular vessel is a diesel-electric gas carrier of substantial size (GT = 144,978, MCR = 40 MW). Since this vessel did not report fuel mix in the survey, it was not reflected in Case 1 and 2 that use reported fuel mix. The reported mean engine load of 14.5% was too low to be considered in modelling of transit conditions and would qualify as manoeuvring instead. The reported average voyage speed of 15 knots and service speed of 19 knots suggests an average engine load of 46% rather than 14.5%. The erroneous entry in the survey for this vessel was removed. Refitting the model produced the same result as shown for reported fuel mix and estimated load (Case 2), as is shown in Table 2.

Fig. 4 shows the absolute prediction error distributions for the two contrasting Cases 1 and 4; survey input data versus default model settings. Although the ship emission model is designed to predict fleet average emissions, it is instructive to examine the prediction errors that will be encountered for individual vessels. The predicted fuel rates represent fleet average values. It is clear that real-world variation will occur. For example, the power demand in the main engine propulsion system can change significantly depending on weather and sea conditions (e.g. currents).

Regarding relative errors for individual vessels, the data suggest that the range of prediction errors (95% confidence interval) lies between about −50% and +75% when default model settings are used to predict fuel consumption in transit conditions. This error is reduced to about ±50% when survey data (reported fuel type and engine load) is used as input. However, survey data are typically not available, so the use of default model settings are most common.

The ship emission algorithms are designed to produce accurate estimates at fleet level, in other words, to make reliable predictions of total emissions for all ships operating in the study area. Table 3 presents the performance results at fleet level, as well as by ship category.

Using the survey data as the benchmark, the prediction error of the ship emission algorithm at fleet level (all ship types) is +12%. This means that the predictions are conservative and that they overestimate reported fuel use during transit with 12 percent on average. The uncertainty in the mean values (standard error) is similar, which suggests that observed vessel specific variability in reported fuel use is replicated in the predictions.

For the individual ship categories, the accuracy is generally similar or better, except for oil tankers. The survey data suggest that emission algorithms for oil tankers potentially underestimate fuel use during transit, but it is noted that the sample size is small with only 5 vessels. Since the majority of survey vessels were bulk carriers, the results are expected to be most robust for this ship type. The data suggest that total fuel use for a fleet of bulk carriers in transit conditions is overestimated with 15%.

3.4. Fuel use at berth

Power requirements for ships are usually reduced once in port, but they still vary depending on the type of ship and its activity, for instance, loading operations (cargo pumps, cranes), hoteling and cargo refrigeration. Auxiliary engines are generally used for electric power production, while the main engines are shut down and the auxiliary boiler generates steam. The main engine is not used when ships are at berth or at anchorage, except for diesel-electric ships, where main engines may be used to generate auxiliary power.

Fig. 5 shows the self-reported fuel use by the auxiliary engines at berth as a function of vessel size (gross tonnage) by type of ship. One vessel reported an unrealistic 800 tonne/day in the survey and was

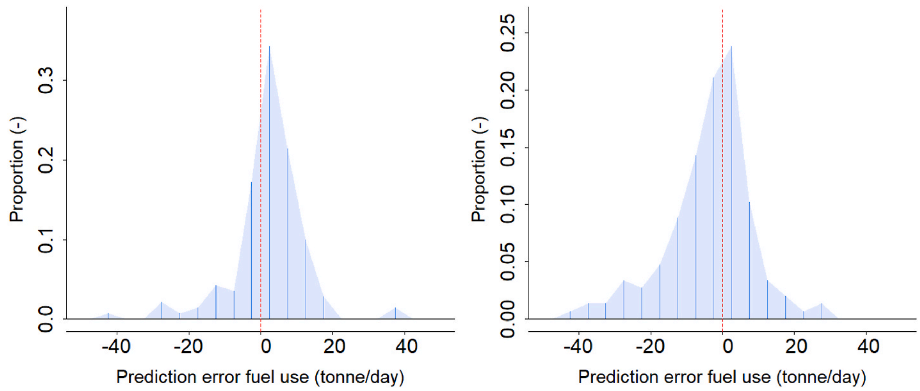

Fig. 4. Absolute prediction error distributions for main engine fuel consumption of individual survey vessels during the voyage to arrival port for Case 1 (left) and Case 4 (right).

Table 3
Summary of mean survey and mean model predictions of main engine fuel use (tonne/day) at fleet level and by ship category during transit conditions, including the standard error of the mean, and the percent difference between survey and model mean values.

Vessel type	Sample size	Survey Mean (±SE)	Model Mean (±SE)	Difference in Means
Bulk Carrier	126	31 (±1.0)	35 (±1.5)	+15%
Container	2	53 (±16.9)	52 (±0.4)	−1%
Cruise	4	73 (±34.8)	80 (±38.7)	+10%
General Cargo	5	17 (±3.3)	16 (±3.5)	−6%
Oil Tanker	5	29 (±5.3)	19 (±5.2)	−33%
Tanker	3	22 (±1.9)	22 (±1.2)	0%
Vehicle Carrier	2	36 (±0.9)	30 (±9.1)	−16%
Fleet	**147**	**31 (± 1.4)**	**35 (± 1.8)**	**+12%**

removed. The average results for bulk carriers and to a lesser extent tankers are based on a significant sample size (n = 115 and n = 8, respectively) and should be relatively robust, as is clear from the confidence intervals. For the other ship types, however, sample sizes are small and the level of uncertainty is increased. It is recommended more survey data are collected for these ship types.

Two cases are considered for berth conditions because average engine load is not used (Table 1). They reflect the use of either the default fuel mix used in the model or reported fuel mix in the survey. Fig. 6 compares reported fuel consumption at berth with predictions. Of the 172 vessels in the survey, 131 vessels (76%) had complete data (at berth conditions) for further analysis (Table 4).

Although the general direction from low to high values is in agreement for model predictions and survey results, the performance of the berth prediction algorithms is significantly lower than the transit algorithms. The use of default or survey fuel mix information hardly affects model performance (SM6). The berth fuel prediction algorithms explain 21% of the variation in the fuel survey data ($R^2 = 0.21$), which equates to a weak to moderate correlation coefficient of 0.46. The mean prediction error is 0.16 tonne/day.

For comparison, Hulskotte and Denier van der Gon (2010) conducted a survey of fuel used on-board of 89 seagoing ships in the Port of Rotterdam in the Netherlands. They also observed a high level of variability in the relationship between GT and reported fuel consumption at berth with low (and sometimes even negative) correlation coefficients. This suggests that the variability in berth fuel consumption is an inherent characteristic of fuel use at berth, rather than an issue with the prediction model.

The fitted parameters for the robust linear regression model are 1.59 ± 0.443 (intercept ± SE) and 0.63 ± 0.111 (slope ± SE). This suggest that the offset (intercept) is statistically significant and that the model tends to overpredict survey data at lower fuel rates (<5 tonne/day) and underpredict survey data at higher rates of fuel use (>5 tonne/day).

Fig. 7 shows the absolute prediction error distributions for the two cases. At individual vessel level, the 95% confidence interval for relative prediction errors lies between about −45% and +115% for both cases.

The ship emission algorithms are designed to produce accurate estimates at fleet level. Table 4 presents the performance results at fleet level and by ship type.

Using the survey data as the benchmark, the prediction error of the ship emission algorithm at fleet level is +6%, which is better than the prediction error for transit (+12%). This means that the predictions are slightly conservative and that they overestimate reported fuel use at berth with 6 percent. The uncertainty in the mean values (standard error) is similar, which suggests that observed variability in fuel use is replicated in the predictions. For the individual ship categories, the errors vary greatly. The data suggest that emission algorithms for oil tankers potentially overestimate fuel use at berth with more than a factor of two, but it is noted that the sample size is small with only 5 vessels. Significant overestimation of about 80% is also observed for container ships and tankers, but the sample size is even smaller. Since the majority of survey vessels were bulk carriers, the results are expected to be most robust for this ship type. The data suggest that total fuel use for a fleet of bulk carriers in transit conditions is underestimated with 6%.

3.5. *Sulphur content and SO_2 emission factors*

Ship exhaust contains sulphur dioxide (SO_2) formed during the combustion of sulphur from fuel oil and lubricating oil. A small fraction (typically 1–2% of fuel sulphur) of this SO_2 is oxidized in the exhaust to form SO_3, which rapidly hydrates to form sulphate and is emitted as particulate matter (Sarvi et al., 2008). The exhaust temperature and the presence of catalytically active species affect the degree of conversion.

The survey included a question regarding the sulphur content (% m/m) of fuels used in main engines, auxiliary engines and auxiliary boilers as per the last Bunker Delivery Note. For the surveyed vessels, high sulphur residual oils are commonly used for both main engines and auxiliary engines. A small portion of ships (n = 8) reports the use of lower sulphur marine distillates such as Marine Gas Oil (MGO) and Marine Diesel Oil (MDO) with a maximum sulphur content of 1 %S. About 90% of the surveyed vessels (n = 153) reported the sulphur content for heavy fuel oil (HFO). The value varied between 0.85 and 5.71 %S, with a mean value of 2.75 %S and a median value of 2.78 %S. Some vessels also reported the use of lower sulphur fuels such as Intermediate Fuel Oil (IFO, n = 6, 0.35–3.21 %S) and Light Fuel Oil (LFO, n = 6, 0.09–0.44 %S).

A weighted average sulphur content was calculated using reported

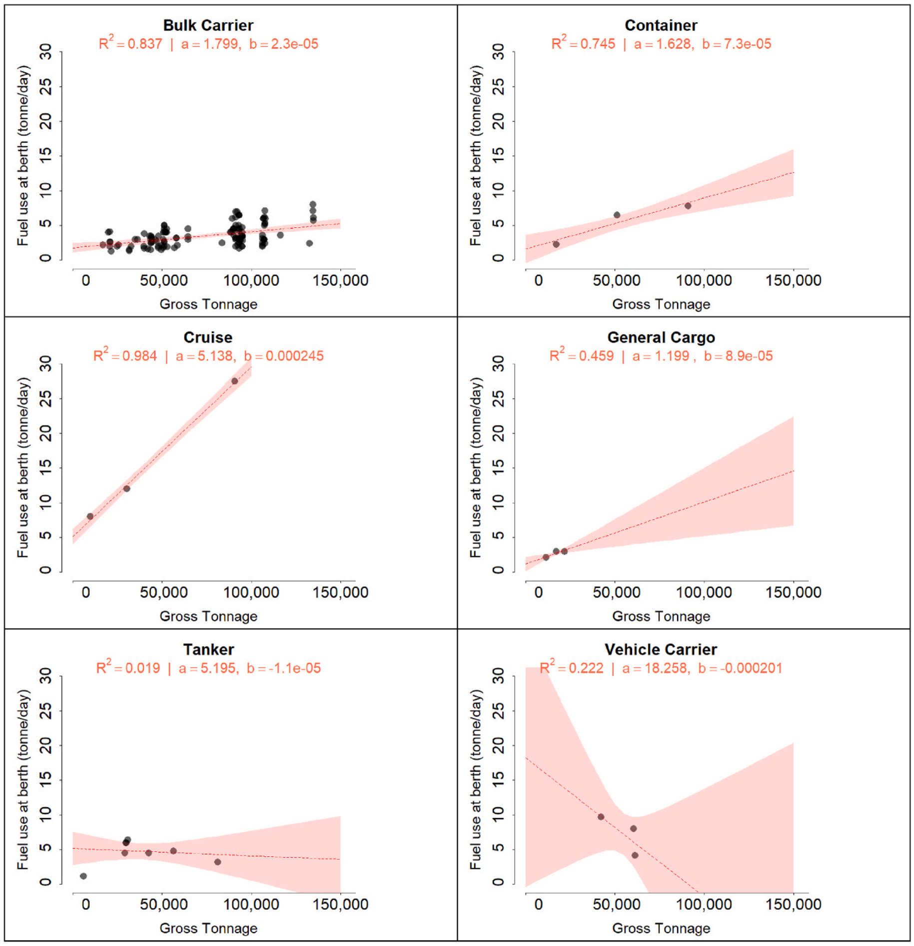

Fig. 5. Correlation between reported auxiliary engine fuel use at berth and ship size for different types of ship. The charts include fitted robust linear regression models (red dotted line) plus the associated 95% confidence interval (red semi-transparent polygon). Fitted parameter values and the Coefficient of Determination are included in the charts.

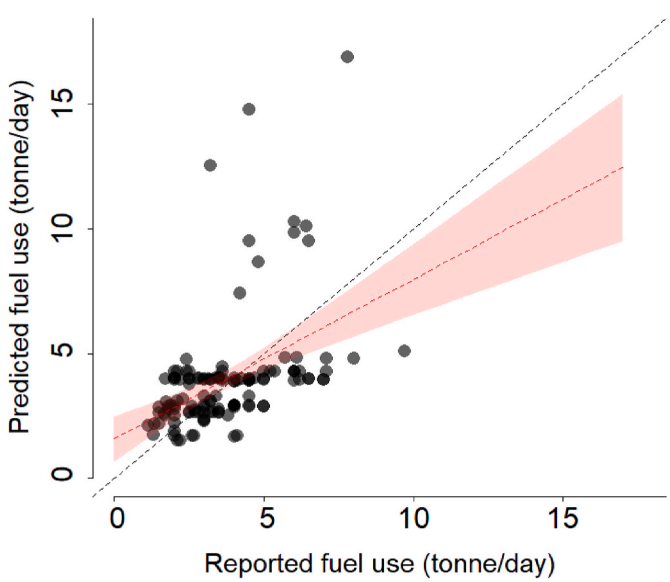

Fig. 6. Predicted versus reported fuel consumption at berth (reported fuel mix). The chart includes a fitted robust linear regression model (red dotted line) and includes the 95% confidence interval (red semi-transparent polygon).

Table 4
Summary of mean survey and mean model predictions of fuel use (tonne/day) at fleet level and by ship category during stationary conditions (at berth), including the standard error of the mean, and the percent difference between survey and model mean values.

Vessel type	Sample size	Survey Mean (±SE)	Model Mean (±SE)	Difference in Means
Bulk Carrier	115	4 (±0.1)	3 (±0.1)	−6%
Container	3	6 (±1.7)	10 (±4.0)	+79%
General Cargo	3	3 (±0.3)	2 (±0.4)	−17%
Oil Tanker	5	4 (±0.8)	10 (±2.2)	+147%
Tanker	3	6 (±0.6)	10 (±0.2)	+74%
Vehicle Carrier	2	7 (±2.8)	6 (±1.2)	−10%
Fleet	**131**	**4 (± 0.1)**	**4 (± 0.2)**	+6%

fuel use as weights for the main engine in transit and auxiliary engines at berth conditions. For main engine operation in transit conditions and auxiliary engines at berth conditions the weighted average sulphur content is 2.68 %S and 2.47 %S, respectively. The non-weighted arithmetic average is similar with calculated values of 2.72 and 2.60 %S, respectively.

The fuel based SO_2 emission factor for transit and berth conditions was then calculated from the weighted average fuel sulphur content, conservatively assuming that all fuel sulphur is converted to SO_2 in the exhaust gases and that the impact of exhaust aftertreatment (such as

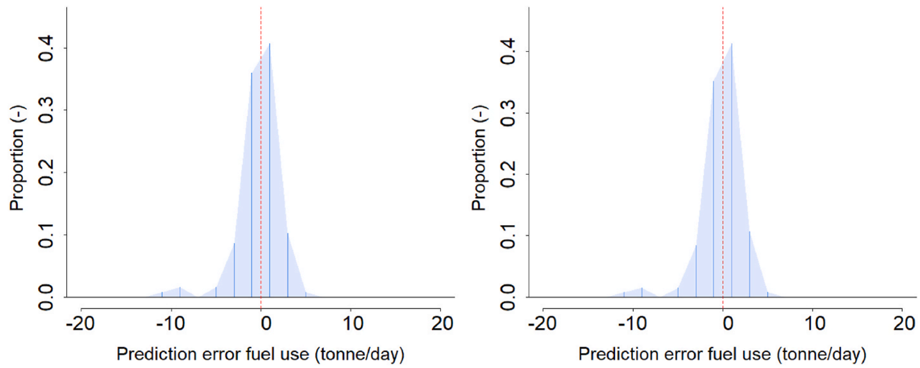

Fig. 7. Absolute prediction error distributions for fuel consumption of individual survey vessels at berth for two cases (left: reported fuel mix, right: default fuel mix).

scrubbers, e.g. Yang et al., 2021) is still negligible in the fleet. The mass percentage of sulphur is multiplied with the ratio of the molecular weight of SO_2 (64 g/mol) to the elemental weight of sulphur in fuel (32 g/mol). The resulting fleet average SO_2 emission factors are 54 g SO_2/kg fuel for transit conditions and 49 mg SO_2/kg fuel for at berth conditions. These values are close (−7% to +1% difference) to the default emission factor in MTEM, 53 g SO_2/kg fuel, which is used for both main engines and auxiliary engines using residual oil.

It is noted that implementation of the global IMO fuel sulphur cap of 0.50% on January 1, 2020 took place after the survey. Compliance and enforcement will be a critical factor determining the effective reduction in fleet average sulphur levels in marine fuels in the coming years (Cullinane and Cullinane, 2013; DNV, 2015), with a certain level of non-compliance reported even in ECAs (Mellqvist et al., 2017). It would therefore be useful to repeat the survey and update the results.

4. Conclusions

Following an evaluation with on-board emissions testing (Smit et al., 2022), the performance of the Maritime Transport Emission Model (MTEM) was evaluated in this study with the results from a survey conducted by the Australian Maritime Safety Authority (AMSA). The survey data were collected for 172 vessels in 21 ports across Australia. The data were examined in detail and unrealistic survey data were removed.

MTEM performs reasonably well during transit at sea regarding the prediction of main engine fuel consumption at fleet level when compared with the survey data (R^2 = 0.6–0.8, MPE = 0.01–0.24 tonne/day). The model (default settings) predicts fuel consumption in transit conditions at fleet level within 12% of the survey results, with generally similar results for individual ship categories. The results suggest that the model predictions for transit conditions are generally robust and conservative at fleet level. For individual vessels, errors are larger, as would be expected. They vary between about −50% and +75% when default model settings are used and about ±50% when survey data (reported fuel type and main engine load) is used as input. Further calibration of the fuel use algorithms for transit conditions is not warranted at this stage, but collection of new survey data will be beneficial, particularly for ship categories that had small sample sizes in the AMSA survey used in this research.

The survey data suggest that the ship emission model for at berth conditions has significant uncertainty for individual ships and ship categories, but that the general direction of the survey data is replicated. Compared to transit conditions, predicted fuel use at berth shows higher variability and reduced performance (R^2 = 0.2, MPE = 0.15 tonne/day). The prediction model tends to overpredict survey data at lower fuel rates (<5 tonne/day) and underpredict survey data at higher rates of fuel use (>5 tonne/day). A bias correction could be applied to future application of the ship emissions model for stationary ships. The fitted regression function can be used to apply a vessel size dependent bias correction to the predicted values, assuming that the survey data are accurate and that the fleet mix is similar for the modelled situation. However, the survey data suggest that the ship emission model for stationary conditions (default model settings) performs reasonably well at fleet level with a prediction error of 6% and appears generally robust. It appears that large prediction errors cancel each other out at fleet level. As a result, bias correction may adversely affect overall accuracy and further survey data collection is recommended.

Reported sulphur content in marine fuels confirms that the default emission factor for sulphur dioxide is a reasonable estimate for emission modelling before 2020. It would be useful to repeat the survey and update the results to reflect the implementation of the new global IMO fuel sulphur cap in 2020.

CRediT authorship contribution statement

Robin Smit: Conceptualization, Methodology, Software, Data curation, Writing – original draft, Visualization, Investigation, Supervision, Writing – review & editingWriting- Reviewing and Editing.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Data availability

Data will be made available on request.

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Appendix A. Supplementary data

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