Greenhouse Gas Emissions from Heavy-Duty Trucking

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Seaports are perceived as multimodal hubs of the logistics supply chain where various transport modes intersect to exchange goods shipped by vessels. Increasing trade and capacity constraints are making this area a major contributor to greenhouse gas (GHG) emissions. National and regional decision-makers perceive port sustainability as a concern while planning GHG mitigation projects. However, to plan and conduct successful GHG management programs, it is critical to first develop an appropriate assessment approach that fits well with the operating and geographical context of the given port. For heavy-duty trucking activities taking place within such ports, several models and methodologies for assessing GHG emissions are available, but their generalization is challenging for many reasons, notably because of the specific features of traffic within the port.

Keywords: non-containerized port ; GHG emissions model ; simulation model ; road transport

1. Introduction

As regional, national, and international economic development expands, the demand for transportation and supply chains grows accordingly. This growth is particularly evident in the port and maritime sector, which has experienced significant development over the past two decades [1]. Seaports serve as multimodal logistics hubs where various transport modes, such as ships, trucks, handling equipment, and locomotives, intersect to facilitate the exchange of goods. Increasing trade volume and capacity constraints contribute to the rise in greenhouse gas (GHG) emissions from this sector, impacting both the climate and public health. Moriarty and Honnery [2] found that transportation accounts for approximately 20–25% of global energy consumption and carbon dioxide (CO_2) emissions, playing a significant role in climate change. In Canada, the GHG emissions from freight transportation saw a 54% increase from 1990 to 2020, with road transport being the leading factor. The transportation sector emitted 159 megatons of carbon dioxide equivalent (CO_2eq) in 2020, representing 24% of Canada's total GHG emissions [3]. Pachakis et al. [4] discovered that heavy-duty vehicles (trucks) are the second-largest source of emissions in ports, followed by ships. Consequently, many ports are investing in GHG mitigation projects to promote and adopt a more sustainable approach to port operations.

Port activities are targeted for GHG mitigation programs, given their role as logistics hubs and the increased volume of trucks frequenting the port. In effect, the 2030 and 2050 horizons successively aim for substantial emission reductions and zero carbon emissions to avoid the worst-case scenarios of climate change. Implementing GHG reduction policies are complicated due to several reasons, including the increasing use of road transportation modes, the energy transition challenges of trucks, and the lack of a standardized and reliable method of assessing emissions, particularly in a port context. The main challenges for the latter reason are related to the unpredictable behavior of trucks inside the port and the choice and availability of attributes that can reliably inform emissions.

2. Greenhouse Gas Emissions from Heavy-Duty Trucking

According to the majority of studies and research, there are two main categories of GHG assessment models: (1) macroscopic models, which can provide estimates of emission rates in large areas, such as the emissions from trucks in a country, based on a macroscopic activity (travel time, distance, etc.); (2) microscopic models, which use instantaneous analysis and adaptation to compute emissions at the scale of a small network (e.g., the emissions of the truck fleet of a company) [5][6][7][8][9].

Macroscopic models, also known as static models or top-down models, as mentioned by [10], are used to calculate a national or regional inventory of emissions. Liao et al. [6] emphasize that "several related parameters in the macroscopic model include: average speed, travel time, distance, and stop time". The drawback of this category is that it generally does not account for factors related to road, driver, and traffic, as reported by [11]. Consequently, planners cannot compare the effects of different scenarios [12]. In the United States, the first two models for estimating emissions from mobile sources that have been used are the MOBILE model (Mobile Source Emission Factor Model) of the Environmental Protection Agency (EPA) and the EMFAC (Emission Factors Model) model of the California Air Resources Board (CARB). To estimate total emission levels, these two models produce emission factors depending on the type and age of the vehicle, its average speed, the ambient temperature, and its mode of operation. However, these models generally fail to capture road, driver, and traffic factors [11][13].

Microscopic models, also known as dynamic or bottom-up models, require a very detailed level of data, such as fuel consumption in different speed ranges and driving conditions; this often leads to very high costs for their implementation. This approach cannot be applied to national emission inventories according to Elkafoury et al. [10]. In the opinion of these authors, microscopic models can be classified into two categories. On the one hand, traffic situation models integrate both speed and traffic conditions (congestion in urban areas) in the estimation of emissions. Among these models, researchers can mention HBEFA (Handbook Emission Factors for Road Transport) and ARTEMIS (Assessment and Reliability of Transport Emission Models and Inventory Systems). On the other hand, instantaneous models combine a traffic simulation model and an emission model to provide a more detailed description of the emission behavior. The PHEM (Passenger car and Heavy-duty Emission Model) is an example of this approach. In their study, Kanagaraj and Treiber [14] distinguished two classes of microscopic models. The first is speed profile emission models, which provide results for local or instantaneous emission factors related to a single vehicle. The second is modal emission models, which are based on the vector e(t) of instantaneous emission factors as a function of speed and instantaneous acceleration modes.

Barth et al. [15] introduced an additional approach to those mentioned above: meso-models, which lie between the macroscopic and microscopic approaches and aim to combine the advantages of both. The consumption calculated using mesoscale models reflects the average consumption of a class of vehicles, which often results in some divergence of results when considering a specific vehicle.

Research works have presented a wide range of specific and accurate fuel consumption models that have been integrated into traffic simulation models while relying on a wide range of assumptions and scenarios to estimate emissions. Indeed, simulation is a tool that enables the construction of an artificial environment with the available data and the exploration of the effect of a restricted number of parameters [16][17]. Simulation is frequently used by researchers to analyze and model various problems concerning transport systems [18]. Arango [19] states that “the use of simulation models for seaport management is very common”. Using multiple modeling paradigms, simulation models show detailed real-world truck operations and can be used to test different operating scenarios as well as to assess, measure, and predict emissions. The simulation model incorporates all appropriate characteristics, such as service time, working rules, and working hours [20].

AlKheder et al. [21] utilized PTV Vissim simulation software to evaluate two scenarios at Kuwait’s Shuwaikh port. The first scenario reflected the port’s initial state without changes, while the second involved a comprehensive transformation of road infrastructure and port operations. A comparison revealed significant improvements in all port operations for the second scenario. For instance, there were an average of 483 stops along a travel period of 3600 to 4500 s in the first scenario, while the future scenario allowed them to reduce the number of stops to between 250 and 404 stops, with an average of around 330 stops. The authors also confirmed the latter scenario’s effectiveness in reducing truck emissions by almost half (48.9%) due to improved port operations. One of the most frequently used performance indicators in marine terminals is the time in the system (TS) [22][23][24]. Azab and Eltawil [25] defined the TS as the time from the truck’s arrival at the terminal gates to the time of departure from the port. Chen et al. [26] obtained a reduction in truck TS from 100 to 40 min at port terminals by using a mathematical optimization model. Rajamanickam and Ramadurai [27] indicated that the TS in a terminal for loading/unloading is around 1 h (h), which is similar to the median TS (51 min) of Los Angeles—Long Beach’s port [28].

According to Neagoe et al. [29], the increase in road freight flows at a bulk cargo maritime terminal in Australia has a significant impact on the TS. It has been observed that trucks can be continuously loaded at the terminal within 10 to 12 min, yet the overall TS for trucks typically exceeds 60 min and, in some instances, extends up to 150 min. It is also noteworthy that approximately 95% of trucks are unloaded within the first hour after arriving at the terminal.

Azab and Eltawil [25] developed a discrete event simulation model to study the effect of various truck arrival patterns on the TS. Consequently, a maximum speed limit of 18 km/h and a triangular distribution for processing time, spanning 5, 10, and 15 min, were considered. Huynh et al. [30] observed that the average processing time in a terminal at the port of Houston for each truck was 3–4 min. Rusca et al. [31] mentioned that the arrival time between trucks is assumed to be constant (1, 2, or 5 min). Vlugt [32] used an exponential distribution of truck service times with rates of 0.33, 0.5, and 0.67, which were derived from the three service times (20, 30, and 40 min). In the same article, the result of the simulation shows a small difference between Poisson and uniform arrivals in the average waiting time. In the case of Poisson arrivals, the average daily waiting time per trucker is assumed to be 11.14 min vs. 10.36 min for uniform arrivals.

Harrison et al. [33] conducted interviews with truck drivers at the Port of Houston, Texas, and found that waiting times inside the terminal could sometimes exceed 2 h. The average waiting time reported was 31 min, with a median of 20 min and a standard deviation of 29 min. Lazic [34] revealed that trucks are responsible for approximately 70% of emissions at container terminals, primarily due to prolonged waiting times and idling engines for air conditioning or heating purposes.

Through an optimisation model, Chen et al. [35] reported a theoretical reduction in trucks’ waiting time from 103 to 13 min on average. Sgouridis et al. [36] produced a simulation model able to simulate several working days of a container terminal’s import area. Thus, they used average parameters related to truck activity, such as truck’s loading/unloading time (0.6 min), speed outside the stacking yards (15 km/h), and speed inside the stacking yards (6.6 km/h). Zhang et al. [37] noted that the nominal speed of trucks in inland ports and terminals is about 12.96 km/h.

The two modes of truck operations commonly cited by researchers are the standby mode, during which the truck's engine is idling, and the travelling mode. In multimodal terminals, a large number of trucks are put on standby for a long time either to load or unload goods, or for other activities. One can cite the example of a large proportion of the 458,000 American long-haul trucks, which travel more than 500 miles per day and can be on standby between 3.3 and 16.5 h per day according to Stodolsky et al. [38].

Chen et al. [35] aimed to reduce emissions from trucks at maritime container terminals by creating a model that addresses the truck assignment problem. Their model minimizes both waiting time and the total number of arrivals. The study evaluated truck emissions with a focus on waiting time, revealing that a minor adjustment in truck arrival times, such as shifting 4% of total arrivals from peak to off-peak hours, could significantly reduce emissions from idling trucks—especially at access gates—by up to a third.

Okyere et al. [39] highlighted the importance of integrating environmental concerns, such as CO_2 emissions, into the development of sustainable transport systems. In the United States and as part of a San Pedro Bay Port emissions inventory to estimate annual GHG rates, Starcrest Consulting Group [40] used the California Air Resources Board (CARB) model. Although the latter develops "low idle" and "high idle" emission rates, the "low idle" rates have only been used in the emissions inventory. Indeed, these rates are "indicative of a truck in a queue" for loading or unloading, while the "high idle" rates are intended to reflect the activity associated with trucks in the port areas.

The accurate quantification of GHG emissions from trucks within port facilities requires a multifaceted approach. While there are several models in the literature for assessing the carbon footprint in a port context, studies addressing GHG emissions associated with truck states (movement and waiting) within the non-containerized port enclosure are rare. On one hand, most studies tend to calculate and mitigate emissions at the gates rather than within the port itself. This can be explained by the complexity of the environment, the diversity of activities, and the dispersion of emission sources inside the port, making data collection challenging. On the other hand, most of the research focuses solely on truck movements, while emissions from waiting, often underestimated and neglected, are equally crucial. Indeed, emissions generated by truck movements are generally easier to measure and quantify than those related to truck waiting, which vary considerably depending on various factors such as traffic congestion and engine regimes (slowing down, stopping, and starting). Due to this variability, accurately quantifying emissions related to truck waiting can be challenging. Furthermore, the existing literature focuses on investigating the carbon footprint within the framework of containerized ports, while few studies address the carbon footprint in the context of non-containerized ports. This highlights a notable gap, leaving room for exploration and analysis in the realm of non-containerized ports.

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