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Fuel consumption estimation in heavy-duty trucks: Integrating vehicle weight into deep-learning frameworks

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ABSTRACT

Insufficient consideration of vehicle weight dynamics during real-world driving could lead to inaccurate fuel consumption estimates. This study examined the impact of vehicle weight on fuel consumption rate (FCR) by analyzing extensive, high-resolution operating data obtained from 162 heavy-duty trucks (HDTs). An engine output power-based (EOP) model, an artificial neural network (ANN) model, and a long short-term memory-convolutional (LSTM-Conv) model were developed and contrasted with conventional vehicle specific power (VSP) and Virginia Tech Microscopic (VT-Micro) models. The results indicated a significant, non-linear relationship between weight and FCR. Compared to 5-ton trucks, FCR for trucks weighing 15–25 tons and 45–55 tons increased by 290% and 755%, respectively, under low-speed and positive acceleration conditions. The LSTM-Conv model outperformed the VSP, VT-Micro, and EOP models, achieving MAPEs of 9.81% for FCR and 1.49% for trip fuel economy estimation. The deep-learning models exhibited enhanced stability across varying speeds, accelerations, and vehicle weights.

1. Introduction

The precise prediction and estimation of the instantaneous fuel consumption rate (FCR) of vehicles is a cornerstone for the adoption of energy-saving technologies like eco-driving and eco-routing (Zhou et al., 2016; Ma et al., 2019; Miotti et al., 2021; Zhang et al., 2022b), as well as for the reduction of carbon dioxide emissions (Xu et al., 2021; Wang et al., 2022a). Existing fuel consumption models often fail to fully consider the complex effects of external variables, such as vehicle weight, on fuel consumption in real-world driving scenarios, leading to potential uncertainties (Zhang et al., 2017; Wang et al., 2021b; Rosero et al., 2021). Furthermore, these models are typically developed and evaluated under limited vehicle operating data and constrained driving conditions, resulting in a lack of comprehensive validation across different vehicle types (Moradi and Miranda-Moreno, 2020).

Fuel consumption is affected by various internal and external factors, such as vehicle-related elements (e.g., engine, transmission, and load), driving behaviors, road conditions, and environmental factors (Boriboonsomsin and Barth, 2009; Rahman et al., 2013;

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Table 1
Literature review on instantaneous vehicle fuel consumption estimation.

Authors	Methods/Models	Vehicles and Weight	Sample Size	Features/Inputs	Estimation Precision
(EPA, 2023)	MOVES	Various	Not specified	Speed, acceleration, jerk, mass, road grade, vehicle type, road type, etc.	Not specified
(An et al., 1997; Barth et al., 2004; Scora and Barth, 2006)	CMEM	Over 300 vehicles, including LDVs and LDTs	Not specified	Speed, acceleration, road grade	Not specified
(Rakha et al., 2004)	VT-Micro	43 LDVs and 17 LDTs	Not specified	Speed, acceleration	Not specified
(Rakha et al., 2011)	VT-CPFM	1 LDT and 2 LDVs (1.2 to 2.2 tons)	Approximately 2,000 s per vehicle	Speed, acceleration	R^2: 0.90–0.97
(Wang and Rakha, 2017)	VT-CPFM	8 HDTs (7.0 to 8.1 tons)	238,893 operating data records	Speed, acceleration	R^2: 0.66–0.87
(Peng et al., 2022)	Engine-based Correction Model (ECM)	4 HDTs (15.0 to 18.8 tons)	46,320 OBD data records at 1 Hz	Speed, acceleration, engine speed, engine torque, and road grade (from GPS)	MAPE:12.83–24.71 %
(Huang et al., 2022)	Model 1: Speed and VSP Coupling Model, Model 2: New Interpretations for Vehicle-Specific Power	661 LDVs	Over 679 million second-by-second records	Speed, acceleration	Average error: 9.7 % for model 1, 8.1 % for model 2
(Zhang et al., 2023)	VAJ	1 LDV	16,350 calibration, 19,269 validation records from OBD at 3 Hz	Speed, acceleration, jerk	MAPE: 12.30 %; RMSE: 0.0047 L/2km; R^2: 0.9575
(Saerens et al., 2013)	Power-based, Linear torque-based, Non-linear torque-based, Linear load-based, Non-linear load-based	Chassis Dynamometer: 6 vehicles; On-road: 8 vehicles	Engine Dynamometer: 500 points; On-road: 2500–3000 data points per vehicle	Speed, engine speed, engine torque, road grade, vehicle power, engine load, and traction force.	Liner torque-based R^2: 0.8188–0.8900; RMSE: 32.55–36.52 mg/s; Power-based: R^2: 0.7887–0.8563; RMSE: 37.47–46.18 mg/s; Linear load-based: R^2: 0.8891–0.9077; RMSE: 31.74–32.63 mg/s
(Zhou et al., 2017)	BIT-TFCM	Not specified	CarSim and MATLAB/Simulink	Speed, acceleration, engine speed, and engine torque	Not specified
(Rui and Hui, 2022)	BIT-DIS	1 LDV	52,293 records from Argonne National Laboratory's D3 database at 10 Hz	Speed, acceleration, engine speed, and engine torque	MAPE: 15.46 % for UDDS & US06, 12.58 % for Highway driving cycles
(Liu and Jin, 2023)	BIT-SVR	1 LDV	52,394 records from Argonne National Laboratory's D3 database at 10 Hz	Speed, acceleration, engine speed, and engine torque	MAPE: 13.69 % for UDDS & US06, 10.78 % for Highway driving cycles
(Perrotta et al., 2017)	SVM, RF, and ANN	1,110 articulated trucks	14,281 records of 60 s or one-mile trajectories	14 features including vehicle weight, road grade, speed, acceleration, start torque, end torque, engine revolutions, road curvature radius, road surface macrotexture, etc.	R^2: 0.83 for SVM, 0.87 for RF, 0.85 for ANN
(Abediasl et al., 2023)	RF, ANN	4 vehicles include a hybrid electric sedan, a full-size pickup truck, a conventional compact SUV, and a PHEV SUV	OBD data from highway (90 min) and urban (36 min) routes at 2 Hz	Engine load, engine speed, intake manifold absolute pressure, throttle position, air–fuel equivalence ratio, and engine coolant temperature	RF: RMSE: 4.17–7.42 g/min (urban), 4.68–11.01 g/min (highway); ANN: RMSE: 7.53–24.8 g/min (urban), 9.71–21.21 g/min (highway)
(Fang et al., 2019)	FuelNet (CNN and GAN)	47 logistics vehicles	Approximately 100,000 data records	Speed, torque	MAE: 4.78 L/h; RMSE: 7.145 L/h
(Wang et al., 2021a; Wang	FuelNet (LSTM)	1 LDV	Approximately 20,000 records from OBD and GPS at 10 Hz.	Speed, acceleration	R^2: 0.858–0.983; RMSE: 0.073–0.468 L/100 km; RE: 0.014–0.053

(continued on next page)

Table 1 (*continued*)

Authors	Methods/Models	Vehicles and Weight	Sample Size	Features/Inputs	Estimation Precision
et al., 2023)					
(Kabir et al., 2023)	ARIMA, LSTM	1 LDV	12,885 OBD records; 56,317 probe vehicle trajectory records.	Speed, elevation	ARIMA: RMSE: 0.5215 Gal/h; MAE: 0.4013 Gal/h; SMAPE[a]: 29.387 %; LSTM: RMSE: 0.3562 Gal/h; MAE: 0.2188 Gal/h; SMAPE: 14.741 %
(Kan et al., 2022, 2020)	LSTM	1 HDT (8.0, 13.0, 29.4 tons)	12 test runs, producing 3,600 to 18,000 s of data per run from CAN-bus at 10 Hz.	The sum of all resistance, the force available for truck acceleration, mass, speed, acceleration, road grade, aerodynamic resistance, rolling resistance, grade resistance, and signal of the vehicle accessories states.	NRMSE[b]: 13.71 % R^2: 0.94
(Liu et al., 2023a)	linear regression (LR), polynomial regression (PR), MLP, CNN, LSTM, CNN-LSTM, and AutoML	VT dataset: 3 trucks; EMS dataset: 38 trucks; IFM dataset: 1 truck.	EMS: 36,419,608 records at 10 Hz; IFM: 872,844 records at 20 Hz.	VT: CO_2, CO, HC, NOx, speed, and engine; EMS: engine speed, throttle, torque; IFM: engine speed, engine torque, engine torque loss, current gear position, longitudinal acceleration, lateral acceleration, retarder torque	CNN-LSTM R^2: 0.9260, 0.9944, 0.9988 for VT, EMS, and IFM datasets, respectively.
(Xu et al., 2018)	ECI, GRNN	6 trucks	Truck operating data from preinstalled internet devices with 2–5 s resolution	ECI: speed, acceleration; GRNN: mean speed, the standard deviation of speeds, peak speed, bottom speed, acceleration share, deceleration share, cruise share, etc.	ECI: RMSE: 0.051–0.054 L; RE: 0.093–0.097 L; GRNN: RMSE: 0.053–0.054 L; RE: 0.089–0.097 L
(Moradi and Miranda-Moreno, 2020)	cascaded machine learning model (SVR and ANN)	27 LDVs	5,400 records per vehicle	Speed, acceleration, road grade	Accuracy: 83 %

[a] Adjusted MAPE or symmetric MAPE.
[b] Normalized RMSE.

Boriboonsomsin et al., 2018; Zhou et al., 2016; Yu et al., 2016; Fan et al., 2022, 2023). Conventional vehicle- or engine-based (or vehicle dynamic-based) fuel consumption models, primarily focused on fundamental factors such as vehicle speed and acceleration, fall short of capturing the comprehensive various fuel impact factors due to their model complexity constraints (Zhou et al., 2016; Huang et al., 2022). In contrast, machine learning- or deep learning-based models are adept at capturing complex, multi-dimensional, and non-linear relationships among various factors (He et al., 2021; Wang et al., 2021a; Li et al., 2022; Abediasl et al., 2023; Noroozi et al., 2023). To achieve higher accuracy and reliability in fuel consumption estimation, these models incorporate a broader range of factors, including vehicle speed, acceleration, engine speed, engine torque, and indirect factors like road and weather conditions. However, owing to the challenges of gathering comprehensive data on factors influencing fuel consumption, most current machine learning- or deep learning-based models still depend on vehicle and engine operating characteristics as input. Other factors, particularly vehicle weight, have yet to be integrated into these models.

Vehicle weight, a critical yet underrepresented factor in fuel consumption modeling, significantly impacts fuel consumption. Studies have indicated that the addition of a 100 kg load to light-duty vehicles (LDVs) can lead to a 5–9 % increase in fuel consumption (Fontaras et al., 2017; Fan et al., 2023). Notably, fully loaded heavy-duty trucks (HDTs) may demonstrate fuel consumption or carbon dioxide emissions over 200 % higher than those of unloaded trucks (Wang et al., 2021b; Kan et al., 2022). HDTs often experience frequent and substantial weight fluctuations due to the nature of their goods-loading and unloading activities. An HDT with an unloaded weight of 18 tons may increase to a total weight of 50 tons when fully loaded, and in rare circumstances, it may even surpass 100 tons. Incorporating vehicle weight data into fuel consumption models, particularly for HDTs, is of great significance to enhance model precision and applicability.

Vehicle weight is often regarded as a constant value in model calibration due to the complexities of calibration and the limited availability of fine-grained weight data. This oversight has restricted the thorough evaluation of vehicle weight's effect on model performance. Besides, the lack of extensive and detailed vehicle operating data and corresponding weight information has hindered the investigation of the complex connection between vehicle weight and FCR. Insufficient understanding of the vehicle weight's effect on fuel consumption will likely impede the development of high-precision fuel consumption models and their practical implementation.

Another significant constraint of existing models is their vehicle-specific nature. Derived from limited datasets that only cover certain types of vehicles and specific driving conditions, these models potentially lack reliability and accuracy when applied to a wide range of vehicle categories.

Given these challenges, there is a growing demand for high-resolution quantitative analysis of the impact of vehicle weight on FCR (especially in each speed and acceleration condition) and a high-precision and robust fuel consumption model to facilitate fuel efficiency and reduce carbon emissions. Specifically, this model is supposed to comprehensively incorporate multiple fuel consumption impact factors, preferably including vehicle weight, to achieve higher accuracy under complex real-world driving conditions. Furthermore, the model needs to be engineered with strong capabilities that can be extended to cover a more comprehensive range of vehicle types and driving situations to ensure its broad applicability.

To bridge this research gap, this study aims to construct a high-precision deep learning model for estimating the FCRs of a fleet of vehicles by integrating vehicle operating data, technical characteristics, and weight information, as well as investigating the holistic effects of vehicle weight on FCR and overall trip fuel economy. Model development and validation are carried out based on an extensive dataset consisting of more than 4 million vehicle operating records from 162 HDTs, collected on a second-by-second basis. The data is collected using on-board diagnostic (OBD) devices, covering a week, and encompassing diverse real-world driving conditions, with a fine-grained and detailed range of vehicle weights varying from 5 tons to 50 tons. This study makes the following contributions:

1) Based on large-scale HDT operating data, this study investigated the effects of vehicle weight on FCR and trip fuel economy from both micro-level (immediate, detailed effects) and macro-level (broader, long-term effect) perspectives. The results highlight vehicle weight's significant and non-linear impacts on FCR across diverse operating conditions.

2) An engine output power-based (EOP) model, an artificial neural network (ANN), and a long short-term memory-convolutional (LSTM-Conv) network were developed. Their effectiveness was evaluated and contrasted with the conventional vehicle specific power (VSP) and Virginia Tech microscopic (VT-Micro) models. The findings indicate that the deep learning models, particularly the LSTM-Conv model, yield strikingly improved prediction performance when integrating vehicle weight information.

3) This study assessed the performances of these models across different vehicle speeds, accelerations, and weight conditions, revealing the superior stability demonstrated by the deep learning models.

2. Literature Review

The recognized importance of accurate fuel consumption estimation has spurred the development of various models, generally classified into vehicle- or engine-based models and machine learning- or deep learning-based models. Table 1 presents a selection of representative models.

2.1. Vehicle- or engine-based fuel consumption models

Conventional vehicle- or engine-based fuel consumption models focus on characterizing vehicle or engine operating conditions based on vehicle dynamics and subsequently calculating the transient FCR using mapping or regression methods. The MOtor Vehicle Emission Simulator (MOVES) model is a prominent illustration. MOVES is a regulatory emission model used to assess mobile source emissions (EPA, 2023). It calculates fuel consumption through weighted averages of emission rates, which are categorized by operating modes defined by VSP. While MOVES can estimate fuel consumption at both macro and micro levels, its accuracy is generally more reliable at the macro level since its base emission rates and adjustments are tailored to reflect "fleet average" conditions rather than the specific characteristics of individual vehicles. Other typical models, such as the comprehensive modal emissions model (CMEM) developed by An et al. (1997) and the VT-Micro model developed by Rakha et al. (2004), employ polynomial functions for the estimation of FCR. The CMEM model describes fuel consumption by incorporating engine speed and output power. The VT-Micro model includes vehicle speed and acceleration, whereas its improved iteration, known as the comprehensive power-based fuel consumption model (VT-CPFM), employs a quadratic function based on output power characteristics to model vehicle fuel consumption (Rakha et al., 2011).

In an effort to overcome the constraints of the restricted operation modes considered by MOVES and its imprecise representations at high speeds, Huang et al. (2022) refined and complemented the VSP-based model by developing two fuel rate models for LDVs. One model integrates speed and VSP, while the other provides novel interpretations of VSP to directly correlate with fuel rate. Peng et al. (2022) introduced an engine-based correction model (ECM) that integrates a feedback loop to correct estimation biases. The findings indicated that the ECM performed better than VT-Micro and CMEM in estimating HDT fuel consumption, owing to the inclusion of the corrective module. Several high-precision models were developed by combining a stable base module with a transient correction module (Zhou et al., 2017; Rui and Hui, 2022; Liu and Jin, 2023). The second derivative of vehicle speed, commonly called "jerk", can be utilized to capture driving behavior. Zhang et al. (2023) introduced a novel fuel consumption model that integrates speed, acceleration, and jerk (VAJ) to estimate fuel consumption using seven quadratic polynomial functions, resulting in reasonable accuracy. Typically, the complex structure of these models poses a challenge for their real-time application. Saerens et al. (2013) employed a subsearch regression method to extract ten well-established polynomial models from prior research and developed nine new models to identify precise and concise models suitable for eco-driving. The evaluation included an analysis of the models' structures and an assessment of their accuracy. The results indicated that low-degree polynomial models are effective in eco-driving applications. However, the findings also emphasized that the prediction performance of these models may not be as reliable in real-world scenarios as in the controlled conditions in which they were originally developed.

Conventional vehicle- or engine-based fuel consumption models possess high interpretability due to their incorporation of specialist physical knowledge (Zhou et al., 2016). However, this interpretability comes at the cost of complex structures. Calibration of model parameters presents a significant challenge, especially when dealing with various vehicle types that demonstrate substantial differences in fuel efficiency. Despite attempts to simplify these models, a considerable number of key parameters must still be preserved to guarantee accuracy (Park et al., 2013; Moradi and Miranda-Moreno, 2020). Therefore, the precision and applicability of these vehicle- or engine-based models heavily depend on thorough calibration across diverse vehicle types and real-world driving conditions.

2.2. Machine learning- or deep learning-based fuel consumption models

In the last decade, advancements in artificial intelligence have greatly improved the computing efficiency of machine learning methods. These methods are effective in addressing complex problems involving high-dimensional and non-linear relationships.

Perrotta et al. (2017) investigated the effectiveness of ANN, random forest (RF), and support vector machine (SVM) in estimating fuel consumption for articulated trucks, using data from truck telematic and road geometry. Fang et al. (2019) designed FuelNet, an innovative model that combines a convolutional neural network (CNN) and generative adversarial network (GAN), to predict the fine-grained FCR. Xu et al. (2018) developed two models to explore the influence of driving behavior on vehicle fuel usage. The first model employed a semi-physical approach centered on the energy consumption index (ECI), while the second model utilized a data-driven approach via a generalized regression neural network (GRNN). Liu et al. (2023a) collected detailed engine data of trucks through engine management system (EMS) and instant fuel meter (IFM) devices. Seven models were developed for truck fuel consumption estimation, including multilayer perceptron (MLP), CNN, LSTM, CNN-LSTM, linear regression (LR), polynomial regression (PR), and automated machine learning (AutoML). The results underscored the importance of high-quality engine data in accurately predicting FCR. Similarly, Wang et al. demonstrated the superior performance of an LSTM-based FuelNet model across diverse driving scenarios, which outperforms VSP, VT-Micro, GRNN, recurrent neural network (RNN), and gate recurrent unit (GRU) models (Wang et al., 2021a; Wang et al., 2023). However, a prevalent limitation of these models is their focus on individual vehicles rather than broader categories. To fill this gap, Moradi and Miranda-Moreno (2020) endeavored to create models applicable to entire vehicle fleets. They utilized a dataset obtained from a diverse fleet of 27 vehicles to construct a cascaded machine-learning model that considered variables like speed, acceleration, road grade, and general vehicle attributes.

Although advanced machine learning- or deep learning-based models offer improved accuracy, they often face criticism for their insufficient consideration of the causality of vehicle dynamics and lack of robust model interpretation. Meanwhile, the effectiveness of these models hinges on the availability of extensive, high-resolution vehicle operating data.

2.3. Summary

Due to their limited structure complexity, conventional vehicle- or engine-based models often struggle to integrate all relevant fuel consumption impact factors. As a result, they tend to prioritize primary factors like speed, acceleration, engine speed, and torque while overlooking other external impacts that compromise their accuracy. Conversely, machine learning- or deep learning-based models can include a broader range of factors, thereby capturing their inherent correlation with fuel consumption and achieving higher accuracy. However, the challenge remains due to the restricted availability of comprehensive fuel-related impact factors, which hinders the precision of these sophisticated models.

Both models are typically calibrated using data from limited scenarios, which may not sufficiently capture the intricacies of real-world driving conditions. The “limited scenario” encompasses two main aspects: (1) The vehicle types included in the available data are limited. As indicated in Table 1, most previous studies are based on experimental data obtained from a limited number of vehicles of a specific vehicle type, typically not exceeding 50. Diverse technical configurations in vehicles, especially in HDTs, such as engine models, displacements, gears, and vehicle weights, contribute to distinct fuel consumption patterns, even under identical operating conditions. Consequently, the suitability of models created for specific vehicle types for application to other vehicle types may be uncertain. (2) The driving conditions covered by the available data are limited. Most of the data used for model development is collected in either laboratory settings (such as engine or chassis dynamometers) or under real-world driving conditions with controlled external variables. In these controlled test scenarios, fuel-related variables such as vehicle weight (load), driving route (road grade and condition), drivers (driving behavior), and environmental conditions (weather and temperature) are typically maintained at a consistent level, with efforts made to minimize their fluctuations and effects on FCR. While this control contributes to the improved accuracy of model verification, it does not comprehensively evaluate the model’s performance due to its inadequate representation of the complexity and dynamics of real-world driving situations.

Furthermore, current fuel consumption models primarily concentrate on LDVs, leaving a gap in the development of models explicitly tailored for HDTs. Many current HDT models do not adequately account for vehicle weight in their construction, disregarding potential fuel consumption variations resulting from significant weight differences. Besides, the absence of high-resolution and fine-grained vehicle weight information hampers the in-depth quantitative analysis of the vehicle weight’s impact on fuel consumption.

The limitations outlined above can be attributed to the limited availability of high-resolution and extensive field data containing instantaneous fuel consumption and its comprehensive impact factors, preferably including vehicle weight. Acquiring such data is essential for developing precise and resilient models and examining the intricate effects of diverse factors on fuel consumption. Specifically, gathering this field data through long-term monitoring of different vehicle types is necessary to ensure the representation of all potential real-world operating situations (Fan et al., 2023). Fortunately, advances in connected vehicle technology have enabled the gathering of extensive, detailed vehicle operating data, enhancing more precise fuel consumption modeling and thorough causality analysis.

3. Method

The study comprehensively evaluated the performance of five fuel consumption models in estimating FCR for HDTs. Two widely used vehicle-based models, the VSP and VT-Micro, were chosen as baseline methods for their popularity and straightforward computational attributes. One engine-based model, EOP, and two deep learning-based models, ANN and LSTM-Conv, were developed to integrate vehicle weight data and improve estimation accuracy.

3.1. Vehicle-based fuel consumption estimation

3.1.1. VSP-based fuel consumption model

The VSP model is favored for its straightforward computation process, measuring power output per unit mass (Jiménez-Palacios, 1999) and considering factors like aerodynamic drag, rolling resistance, and vehicle dynamics (Song and Yu, 2009). FCR remains generally stable with negative VSP values but linearly increases when VSP exceeds 0 kW/ton (Fan et al., 2022). In the VSP model, FCR can be mathematically approximated using the following equations:

$$VSP = \frac{Av + Bv^2 + Cv^3 + mv(a + gi)}{m} \tag{1}$$

$$FCR = \begin{cases} \alpha P_{idle}, VSP < 0 \\ \alpha mVSP + \alpha P_{idle}, VSP \geq 0 \end{cases} \tag{2}$$

where A represents the rolling resistance (kW·s/m); B represents the rotational resistance (kW·s^2/m^2); C represents the aerodynamic drag (kW·s^3/m^3); m represents the vehicle mass (kg); v represents the vehicle speed (m/s); a represents the acceleration (m/s^2); g represents the acceleration of gravity (m/s^2); i represents the road grade (%); α represents the conversion factor between FCR and engine power (mL/s/kW); and P_{idle} represents the idle power (kW).

3.1.2. VT-micro fuel consumption model

The VT-Micro model, another popular vehicle-based model, utilizes speed and acceleration to estimate FCR (Park et al., 2013; Rakha et al., 2004), adjusting for acceleration impacts and ensuring FCR values are non-negative through natural logarithms (Faris et al., 2011). The structure is as follows:

$$\ln(MOE_e) = \begin{cases} \sum_{i=0}^{3}\sum_{j=0}^{3}\left(L_{i,j}^{e}s^{i}a^{i}\right) & a \geq 0 \\ \sum_{i=0}^{3}\sum_{j=0}^{3}\left(M_{i,j}^{e}s^{i}a^{i}\right) & a < 0 \end{cases} \tag{3}$$

where MOE_e represents FCR (mL/s), $L_{i,j}^{e}$ is the regression coefficient for MOE_e at a speed power i and acceleration power j for positive accelerations; $M_{i,j}^{e}$ is the regression coefficient for MOE_e at a speed power i and acceleration power j for negative accelerations; s represents the vehicle speed (m/s); and a represents the vehicle acceleration (m/s^2).

3.2. Engine-based fuel consumption estimation

3.2.1. EOP-based fuel consumption model

Vehicle fuel consumption is inherently linked to the mechanical output generated by its engine. Conventional vehicle-based models typically derive propulsive power by considering speed and acceleration, presuming a direct correlation with the engine's output power. In contrast, the EOP model emphasizes the direct utilization of engine output parameters to represent fuel consumption more accurately. The EOP model's development progresses as follows:

$$EOP = F_e v_e \tag{4}$$

$$v_e = \frac{2\pi r_e N}{60} \tag{5}$$

$$T_e = \frac{F_e r_e}{\eta} \tag{6}$$

$$EOP = \frac{2\pi\eta T_e N}{60} \tag{7}$$

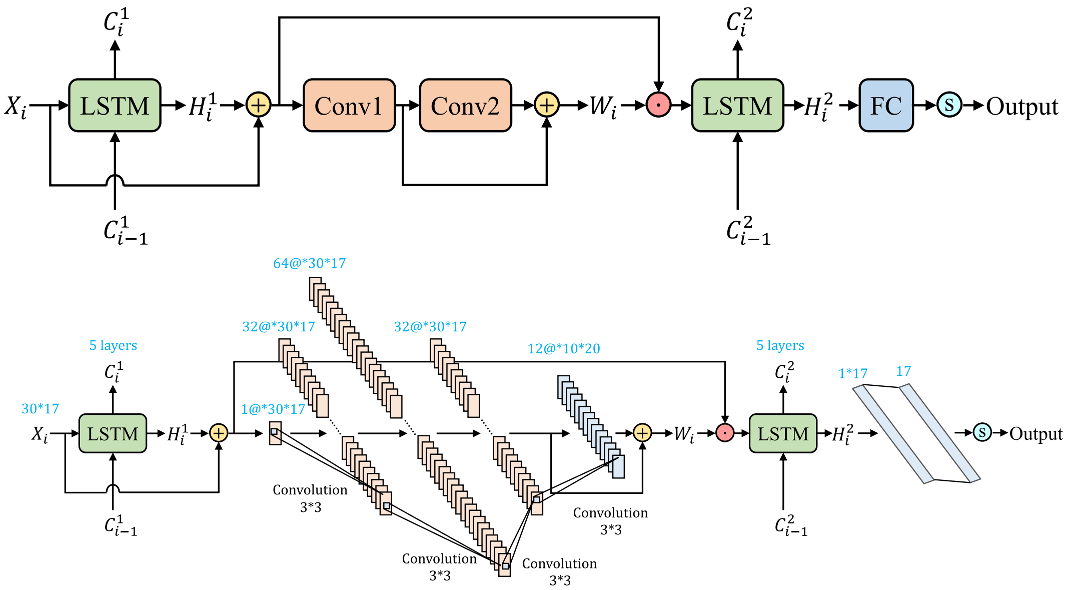


Fig. 1. Structure and calculation flowchart of the proposed LSTM-Conv network.

$$FCR = \alpha(EOP + \beta) \tag{8}$$

where EOP represents the instantaneous engine output power (W); F_e represents the engine output force (N); v_e represents the engine line speed (m/s); r_e represents the force arm of the engine (m); N represents the engine speed (revolution per minute); T_e represents the output torque of the engine (n·m); η represents the driveline efficiency (%); α represents the ratio between FCR and engine power (mL/s/W); and β represents the idle power (W).

3.3. Deep learning-based fuel consumption estimation

3.3.1. ANN network

In this study, we constructed an ANN network with six hidden layers, each consisting of 8, 16, 32, 32, 16, and 8 neurons, respectively. A total of 17 fuel-related features (shown in Table 3) were extracted as input variables. The output layer is designed to produce a single fuel consumption value. Rectified linear unit (ReLU) was chosen as the activation function for the hidden layers, whereas the Sigmoid function was chosen for the output layer.

3.3.2. LSTM-conv network

FCR is impacted by both current and historical vehicle operating conditions (Kabir et al., 2023; Liao et al., 2023; Wang et al., 2023). To effectively capture the intricate interplay of time-dependent variations and interactions among fuel impact factors, a novel LSTM-Conv network was developed for fuel consumption estimation.

The developed LSTM-Conv network utilizes a two-dimensional feature approach that integrates data from multiple time steps to capture both temporal (time-related changes) and spatial (feature interactions) features. LSTM network is employed to capture the time series characteristics inherent in the operating data, while also tackling the challenge of long-range dependencies that are frequently encountered in sequential data tasks. CNN modules are integrated due to their strong proficiency in discerning and extracting complex, intrinsic relationships among features. By integrating the strengths of LSTM and CNN architectures, the proposed LSTM-Conv network is developed to effectively capture the “spatial-temporal” features of the fuel impact factors, thus improving the estimation accuracy.

Additionally, the proposed LSTM-Conv model incorporates attention mechanism and residual network methodologies to enhance its emphasis on key features. The proposed model consists of two LSTM modules and two two-dimensional CNN modules, as illustrated in Fig. 1. The first LSTM module is responsible for acquiring and encoding the time series characteristics of the input features, as well as capturing the historical evolution of vehicle operating conditions. The encoded information H_i^1 is subsequently integrated with the prevailing vehicle operating characteristics X_i^1. At this stage, a sophisticated attention mechanism is employed to evaluate and allocate weights to the features within the space, thereby improving the model’s emphasis on significant aspects. The feature space weights W_i are derived by adding the outputs of the first and second CNN modules. Meanwhile, residual network methodologies are introduced to mitigate the potential issue of overfitting that may arise as network complexity increases. The final output W_i dynamically models the spatial dependencies inherent in the instantaneous vehicle operating data.

The attention map W_i obtained substantially enhances the representational capability of the network. The map W_i is then integrated with the input of the first CNN module, leading to a reweighted spatial-temporal feature map. The enhanced map is subse-

Fig. 2. Data collection (a), test vehicles (b), and vehicle driving trajectories (c) of this study.

quently fed into the second LSTM module, which is responsible for extracting the hidden state H_i^2. Following the extraction of H_i^2, it is flattened and fed into a fully connected layer to derive the final model output. The computational process of the LSTM-Conv network can be concisely articulated as follows:

$$H_i^1 = LSTM_1\left(X_i, C_{i-1}^1\right) \tag{9}$$

$$W_i = CNN_1\left(X_i \oplus H_i^1\right) \oplus CNN_2\left[CNN_1\left(X_i \oplus H_i^1\right)\right] \tag{10}$$

$$H_i^2 = LSTM_2\left[\left(X_i \oplus H_i^1\right) \odot W_i, C_{i-1}^2\right] \tag{11}$$

$$FC_i = \sigma\left(WH_i^2 + b\right) \tag{12}$$

where H_i^1 and H_i^2 are the outputs of the hidden layer of the first and second LSTM modules, respectively; X_i is the input feature; C_{i-1}^1 and C_{i-1}^2 are the cell states of the previous moment of the first and second LSTM modules, respectively; W_i is the attention map; W and b are the weights and bias of the fully connected layer, respectively; and σ is the Sigmoid function.

3.4. Model validation

Four primary metrics were employed to comprehensively evaluate the prediction performance of the proposed models as follows:
(1) Mean Absolute Error (MAE):

$$MAE = \frac{1}{n}\sum_{i=1}^{n}\left|\hat{y}_i - y_i\right| \tag{13}$$

(2) Mean Absolute Percentage Error (MAPE):

$$MAPE = \frac{1}{n}\sum_{i=1}^{n}\left|\frac{\hat{y}_i - y_i}{y_i}\right| \tag{14}$$

(3) Root Mean Square Error (RMSE):

$$RMSE = \sqrt{\frac{\sum_{i=1}^{n}\left(\hat{y}_i - y_i\right)^2}{n}} \tag{15}$$

(4) Coefficient of Determination (R^2)

$$R^2 = 1 - \frac{\sum_{i=1}^{n}\left(\hat{y}_i - y_i\right)^2}{\sum_{i=1}^{n}\left(y_i - \bar{y}_i\right)^2} \tag{16}$$

Table 2
Technical configurations of sample vehicles.

Make	Vehicle Type	Engine Type	Engine Displacement (L)	Maximum Reference Torque (N·m)	Maximum Net Torque (N·m)	Emission standard	Rated Power (kW)	Maximum Gross Mass (kg)
AUMAN	BJ5259XXYY6HPS-01	D6.7NS6B290	6.70	1,200	1,088	China 6	213	25,000
AUMAN	BJ4259Y6DHL-12	X13NS6B520	12.90	2,814	2,493	China 6	382	25,000
FAW	CA3310P27K15L1T4E6A80	WP10H400E62	9.50	2,062	1,885	China 6	294	31,000
FAW	CA4250P1K15T1E6A80	WP10.5H460E62	10.52	2,256	2,085	China 6	338	25,000
FAW	CA5310XLCP77K24T4E6	CA6DM3-56E6	12.52	2,814	2,600	China 6	415	31,000
FOTON	BJ5186XYK-1A	F4.5NS6B220	4.50	950	813	China 6	162	18,000
FOTON	BJ5186XLC-DM1	B6.2NS6B245	6.20	1,100	988	China 6	180	18,000
HOWO	ZZ5257CCYN48CJF1	MC07H.33–60	7.36	1,600	1,400	China 6	240	25,000
HOWO	ZZ4257V324HF1B	MC13H.57–61	13.02	2,800	2,600	China 6	422	25,000
JAC	HFC5251XXYP1K5D52KS	D6.7NS6B320	6.70	1,200	1,188	China 6	231	24,995
JAC	HFC5311CCYP1K5G43S	YCK08350-60	7.70	1,565	1,435	China 6	257	31,000
SITRAK	ZZ5256XXYN56CGF1	MC07H.33–60	6.87	1,600	1,400	China 6	240	25,000
SITRAK	ZZ4256V324HF1B	MC13.48–61	12.42	2,550	2,400	China 6	356	25,000
ZOOMLION	ZLJ5311GJBHT5F	MC07H.35–60	7.36	1,600	1,400	China 6	257	31,000
BAIQIN	XBQ5310ZSLA36D	L9NS6B360	8.90	1,950	1,685	China 6	265	31,000
CHENGLONG	LZ5250XXYM3CB	YC6JA220-50	6.87	1,070	850	China 5	179	25,000
CHENGLONG	LZ4250H5DC1	WP10.5H430E62	10.52	2,197	1,985	China 6	316	25,000
DONGFENG	DFH5180CCYEX5	DDi50E220-60	5.00	850	838	China 6	162	18,000
DONGFENG	DFH4180D2	ISZ520 51	13.00	2,700	2,430	China 5	378	18,000
DONGFENG	DFH1310D8	Z14NS6B560	13.48	2,900	2,620	China 6	418	31,000
HAIDE	CHD5311ZXXZQE6	MC07H.35–60	7.36	1,600	1,400	China 6	257	31,000
SHANQI	SX4259MC4WQ1	WP10.5H430E62	10.52	2,197	1,985	China 6	316	25,000
SHANQI	SX3319HD276	WP12.400E62	11.60	2,149	1,985	China 6	294	31,000
SHANQI	SX4259XD4Q1	WP13.480E62	12.54	2,471	2,285	China 6	353	25,000

Table 3
Valid ranges of vehicle operating data for data quality control.

Num		Contents	Ranges of valid data	Units
1	Observation	Vehicle speed	(0,130]	km/h
2		FCR	[0,100]	L/h
3		Air pressure	[90,110]	kPa
4		Engine net output torque	[0,100]	%
5		Friction torque	[0,100]	%
6		Engine speed	[0,5000]	npm
7		Engine displacement	–	L
8		Maximum reference Torque	–	N·m
9		Maximum net torque	–	N·m
10		Emission standard	–	–
11		Rated power	–	kW
12		Maximum gross mass	–	kg
13		Limited weight[a]	–	kg
14		Vehicle weight	–	kg
15	Calculation	Acceleration	[−5,5]	m/s^2
16		Jerk	[−5,5]	m/s^3
17		EOP	[0,1000]	kW
18		STP[b]	[−50,50]	kW/ton

[a] Maximum legally permitted weight of a vehicle on the road, closely related to the vehicle's number of axles.
[b] Scaled tractive power, with the same calculation as VSP.

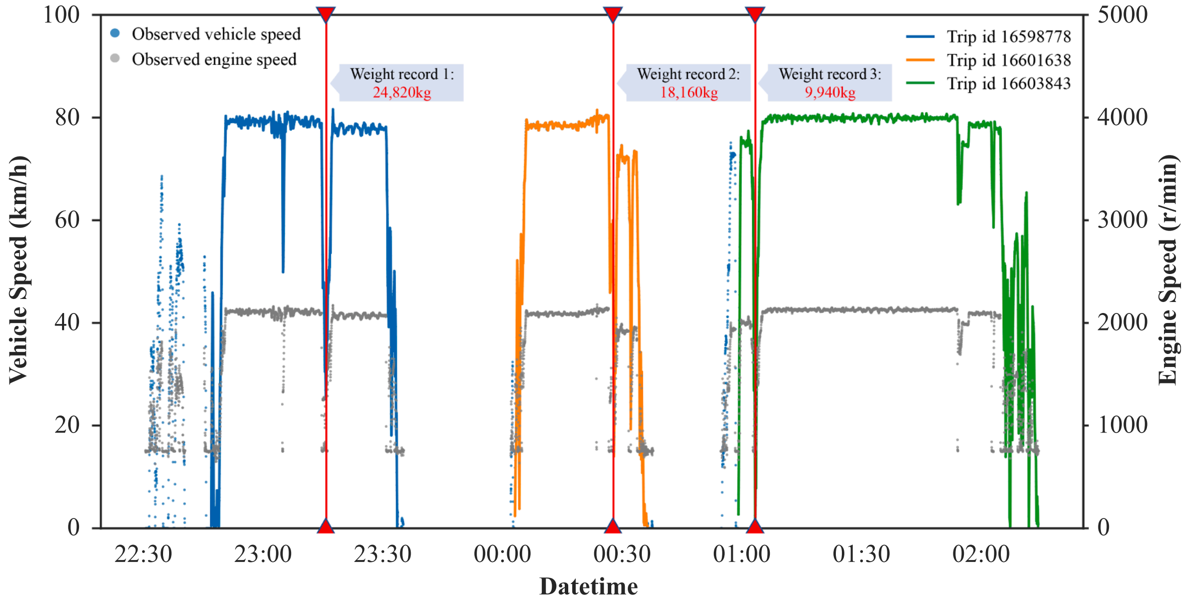


Fig. 3. Trip split and weight matching for a sample vehicle.

where y_i represents the real-world measured FCR (L/h); $\hat{y}_i$ represents the predicted FCR (L/h); $\bar{y}_i$ represents the average FCR of y_i (L/h); and n is the sample size.

4. Data

4.1. Data sources

This study aims to examine the impact of vehicle weight on fuel consumption and to model the fuel consumption of HDTs by incorporating large-scale vehicle operating data with weight information. The field vehicle operating data were gathered in Shandong Province, China, from February 10 to 18, 2023. Specifically, instantaneous vehicle operating data, including speed, engine speed, engine torque, fuel consumption, etc., were collected from 162 HDTs. These trucks were equipped with specialized monitoring devices connected to OBD systems, as illustrated in Fig. 2. The monitoring was conducted at 1 Hz, guaranteeing a detailed and continuous recording of vehicle operating parameters.

Detailed vehicle attributes and engine configurations such as engine displacement, maximum reference torque, maximum net

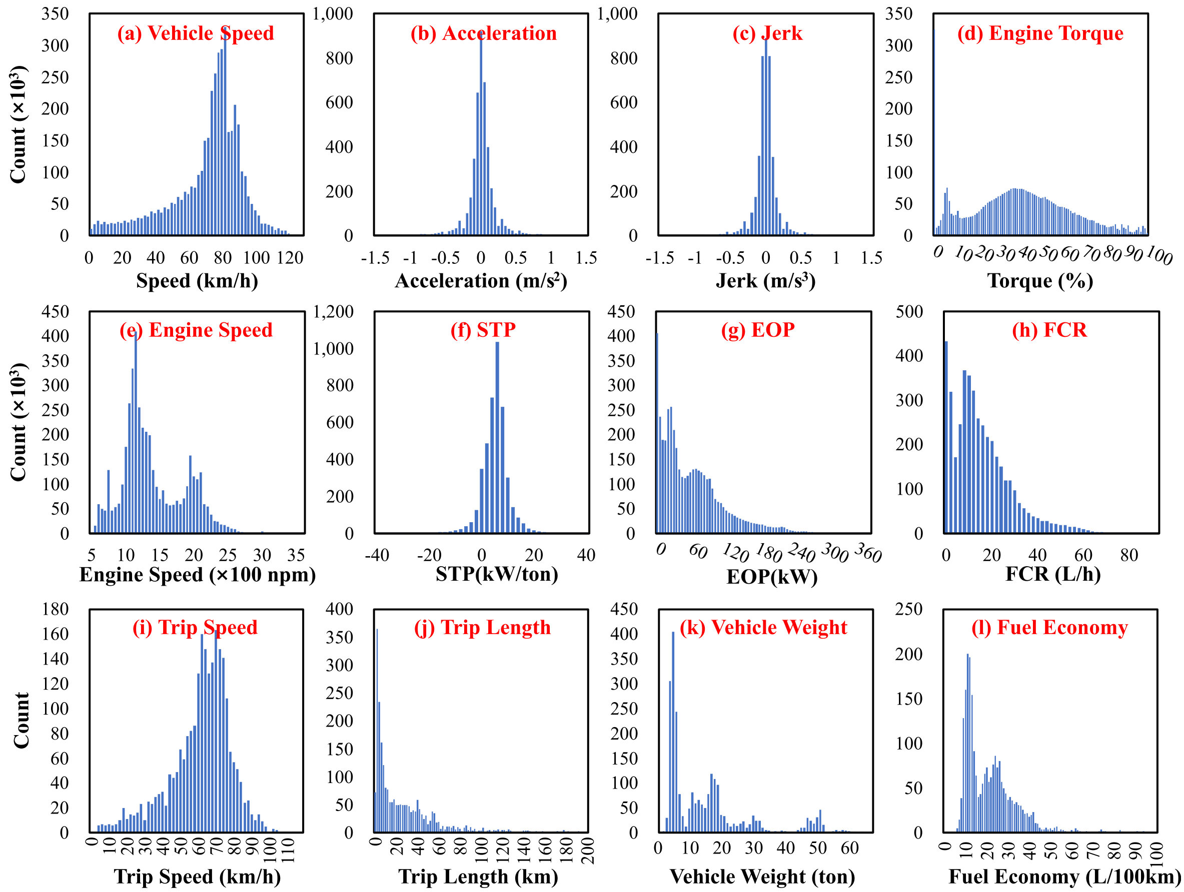


Fig. 4. Distributions of instantaneous vehicle operating parameters and trip characteristics under typical driving conditions.

torque, emission standard, rated power, and maximum gross mass of the 162 HDTs were collected (refer to Table 2 for sample data).

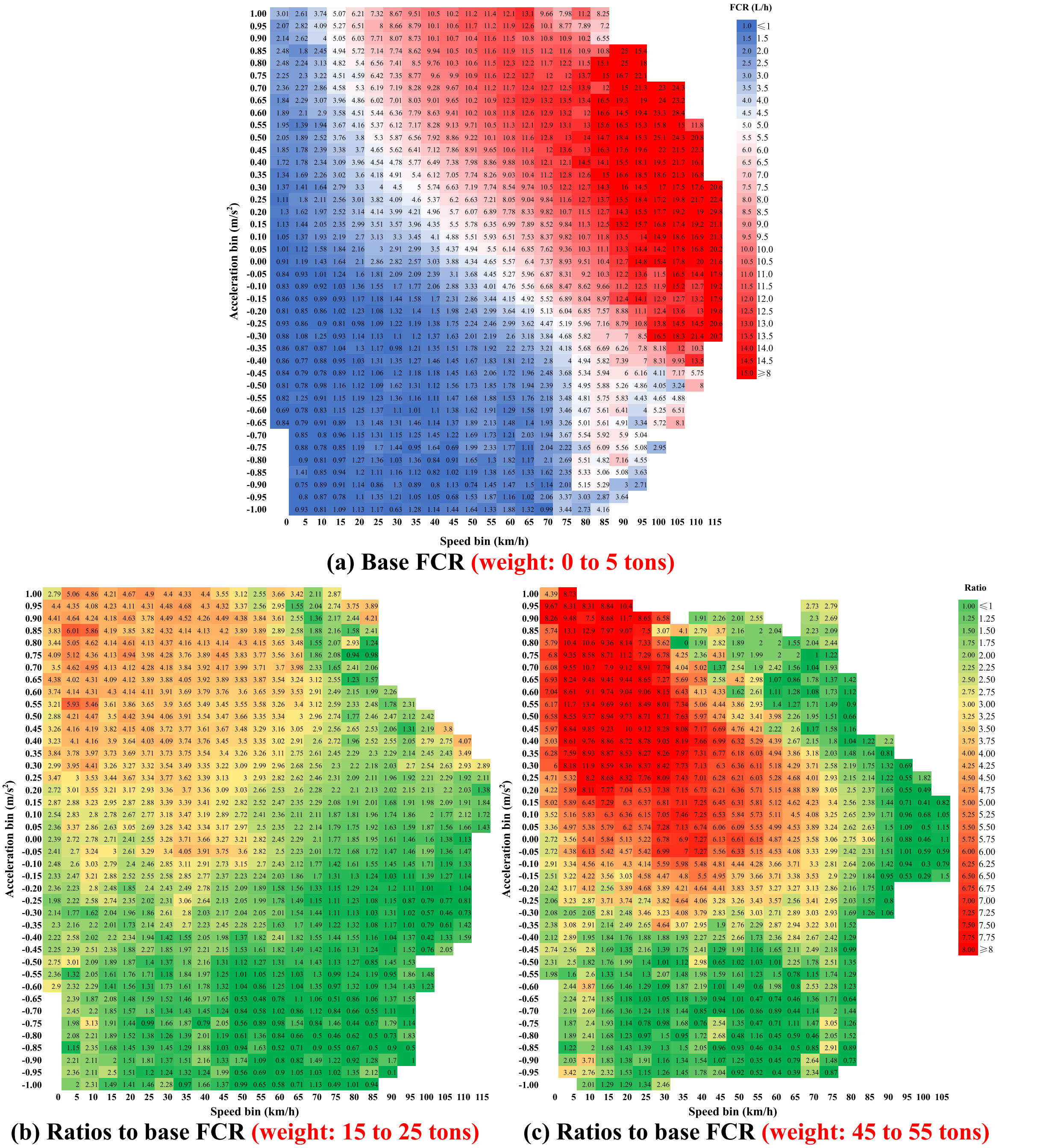
The weight information was sourced from the weighing records of the 162 HDTs. During the test campaign, all HDTs were mandated to adhere to a rigorous weighing procedure to accurately measure their vehicle weight, including cargo, at every instance of goods-loading and unloading. The weighing times, vehicle identification numbers (VIN), and vehicle weight (in kg) were documented and promptly transmitted to the utilized cloud server. The weighing equipment used conformed to regulatory standards and guaranteed accuracy within $\pm$ 5 %, thereby yielding genuine and dependable weighing results.

The weight of HDT fluctuates in real-world scenarios due to goods-loading and unloading, but it remains consistent during continuous driving. A rigorous procedure for matching vehicle weights with corresponding operating data was implemented. A "vehicle trip" was specifically defined as a sustained drive without stops or idling to exclude potential cargo handling. Any period of stationary lasting longer than 10 s was considered a stop. The continuous operating data recorded between two successive stops constituted a trip. We matched the weighing records collected during the trip's start and end times to the specific trip, providing the real-world vehicle weight (as shown in Fig. 3). Any operating data from trips without corresponding weight records was excluded from subsequent analyses.

Following the strict weight-matching process, a dataset comprising 4,249,545 records of vehicle operating data with accurate weight information was maintained from the one-week test campaign. This dataset encompasses approximately 81,761 km of driving distances and 1,180 driving hours, all of which were conducted under real-world driving conditions. Fig. 2 (c) depicts the driving trajectory of the test HDTs, covering a significant portion of the expressway in Shandong Province.

4.2. Data quality control

FCR, speed, and acceleration ranges of a vehicle are usually limited by engine performance and traffic conditions (Zhang et al., 2022a). To ensure data validity, this study considered data falling within the ranges defined in Table 3 as valid. The original data were time-aligned (Wang et al., 2021b) and subsequently screened for outliers. Following examination, it was found that outliers constituted merely 0.18 % (7,987 records) of the original dataset. Given their negligible proportion and the potential complexity of their origins (erroneous recordings, signal loss, etc.), these outliers were considered unsuitable for correction through standard methods like interpolation. Consequently, these outliers were carefully identified and excluded from further analysis. This approach avoids



* The blank spaces denote intervals where insufficient valid data precludes a reliable analysis of the FCR or ratio.

Fig. 5. Comparative analysis of vehicle weight on fuel consumption: Base FCR (a), ratios to base FCR for weight bins 15–25 tons (b), and 45–55 tons (c).

introducing unnecessary complexity or bias that might arise from attempts to correct or incorporate these outliers, and will not significantly impact the results of our study. Fig. 4 illustrates the distributions of instantaneous vehicle operating features and trip characteristics under typical driving conditions. Please note that for clearer visualization of feature distributions, Fig. 4 selectively presents the ranges of typical operating conditions, rather than encompassing the full spectrum of data previously identified as valid in Table 3.

Original vehicle operating data from each trip was split into two sets: 80 % of the initial operating data was allocated to the training

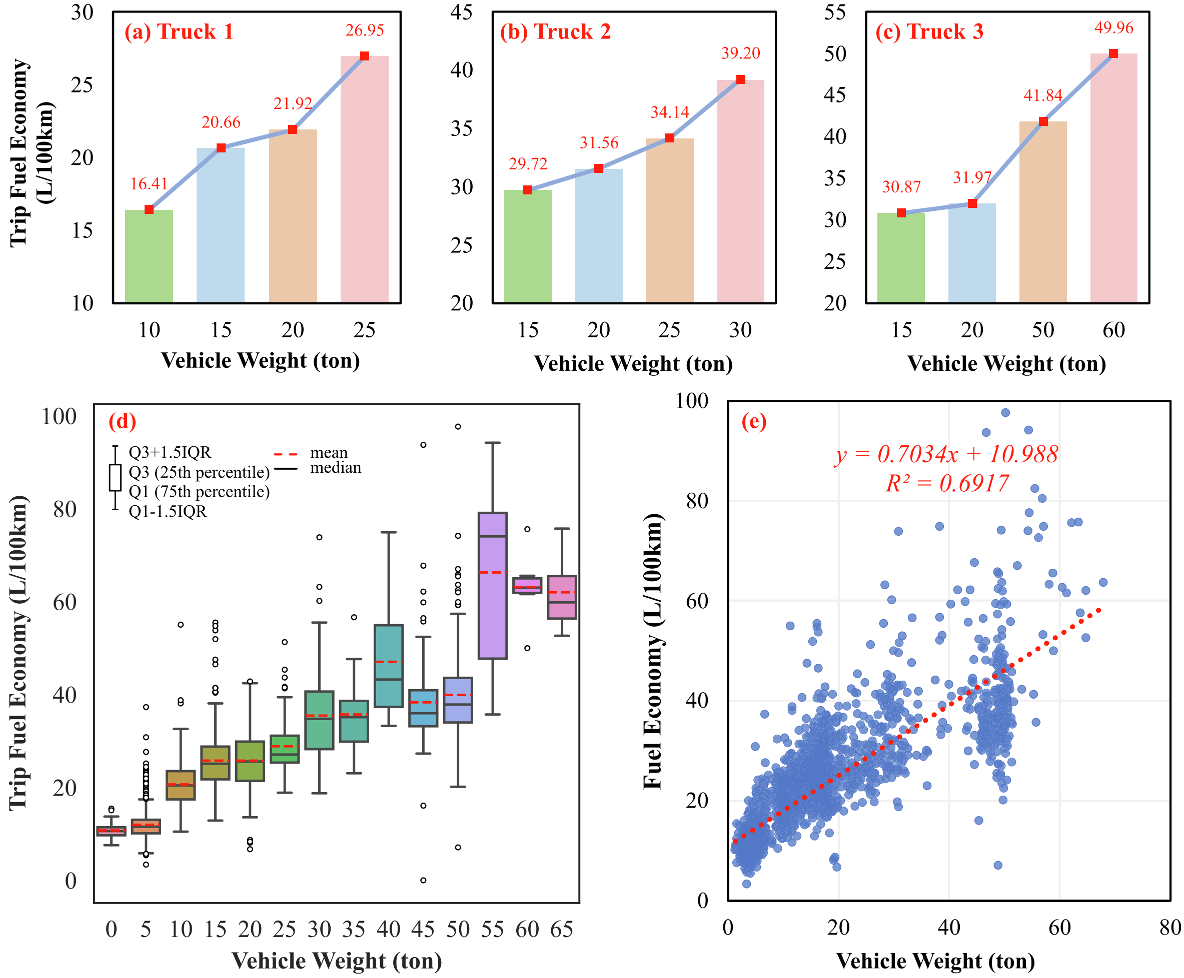


Fig. 6. Correlation between trip fuel economy and vehicle weight.

set, while the remaining 20 % constituted the test set. The training set was utilized for model training and parameter calibration, and the test set was used for evaluating model performance.

4.3. Implementation details

Our experiments were conducted on a computational platform equipped with an Intel Core i7-12700KF CPU (3.60 GHz), 64 GB RAM, and an NVIDIA GeForce RTX 4090 GPU. The software environment was based on Python 3.11.4, with PyTorch 2.0.1 serving as the deep learning framework. CUDA 11.8 was used to leverage GPU acceleration. The sequential length of the input of the proposed LSTM-Conv model is set to 30. Data normalization was applied to both input features (vehicle speed, acceleration, vehicle weight, etc.) and the target variable (FCR) to enhance model convergence speed and performance stability. A dropout layer with a rate of 0.3 was included to prevent overfitting, and the ReLU activation function was used for non-linearity introduction between layers.

Model training was performed using the Adam optimizer with a learning rate of 0.0001, which was chosen based on preliminary experiments that indicated optimal convergence speed and stability. The batch size was set to 512, balancing computational efficiency and training stability. Model performance was evaluated using the MAE as the loss function.

To enhance training efficiency, we implemented an early stopping mechanism that halts the training if there is no improvement in validation performance over 100 epochs. The training of the LSTM-Conv model concluded after 972 epochs, totaling approximately 11 h and 21 min to complete, inclusive of the time taken for validation loss computation at the end of each epoch. The inference time for processing a single input was approximately no more than 10 ms, demonstrating the model's suitability for real-time applications where rapid fuel consumption predictions are essential.

Table 4
Estimation performances of VSP, VT-Micro, EOP, ANN, and LSTM-Conv models of FCR and trip fuel economy.

	Model	Inputs	Test sample size	RMSE (L/h)	MAE (L/h)	MAPE (%)	R^2
FCR	VSP	Speed, Acceleration, Vehicle Weight	485,440[a]	10.0345	6.7108	182.45	0.3634
	VT-Micro	Speed, Acceleration	636,802[b]	9.9693	5.8150	103.92	0.3754
	EOP	Engine Net Output Torque, Engine Speed, Maximum Reference Torque	845,006	4.0270	1.8970	50.58	0.8961
	ANN	The remaining 17 parameters in Table 3, excluding FCR	845,006	2.0941	0.9105	15.17	0.9719
	LSTM-Conv (without weight)	The remaining 16 parameters in Table 3, excluding FCR and Vehicle Weight.	682,068	1.2552	0.6313	10.74	0.9898
	LSTM-Conv	The remaining 17 Parameters in Table 3, excluding FCR	682,068	1.2583	0.5754	9.81	0.9898
Trip fuel economy[c]	VSP	Speed, Acceleration, Vehicle Weight	944	5.8198	3.9946	28.49	0.6253
	VT-Micro	Speed, Acceleration	1,604	6.4284	3.5814	21.75	0.6481
	EOP	Engine Net Output Torque, Engine Speed, Maximum Reference Torque	2,068	1.3273	0.7835	5.49	0.9861
	ANN	The remaining 17 parameters in Table 3, excluding FCR	2,068	0.8872	0.4302	2.31	0.9936
	LSTM-Conv (without weight)	The remaining 16 parameters in Table 3, excluding FCR and Vehicle Weight.	1,540	0.5631	0.2988	1.93	0.9974
	LSTM-Conv	The remaining 17 parameters in Table 3, excluding FCR	1,540	0.4737	0.2254	1.49	0.9981

[a] Model test included only vehicle types with a goodness-of-fit $R^2 \geq 0.6$ in positive VSP bins.
[b] Model test included only vehicle types with more than 10,000 data points in the training dataset and a goodness-of-fit $R^2 \geq 0.6$.
[c] Model test included only trips with a driving distance of more than 500 m.

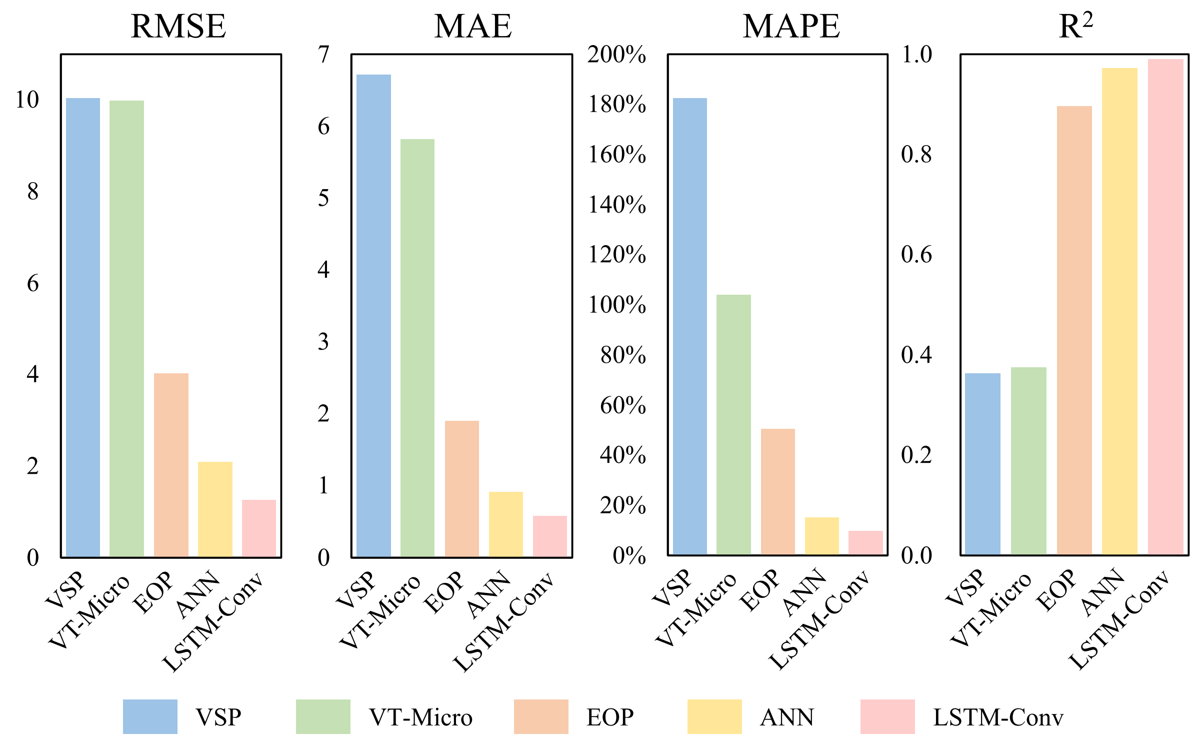


Fig. 7. FCR estimation performances of VSP, VT-Micro, EOP, ANN, and LSTM-Conv models.

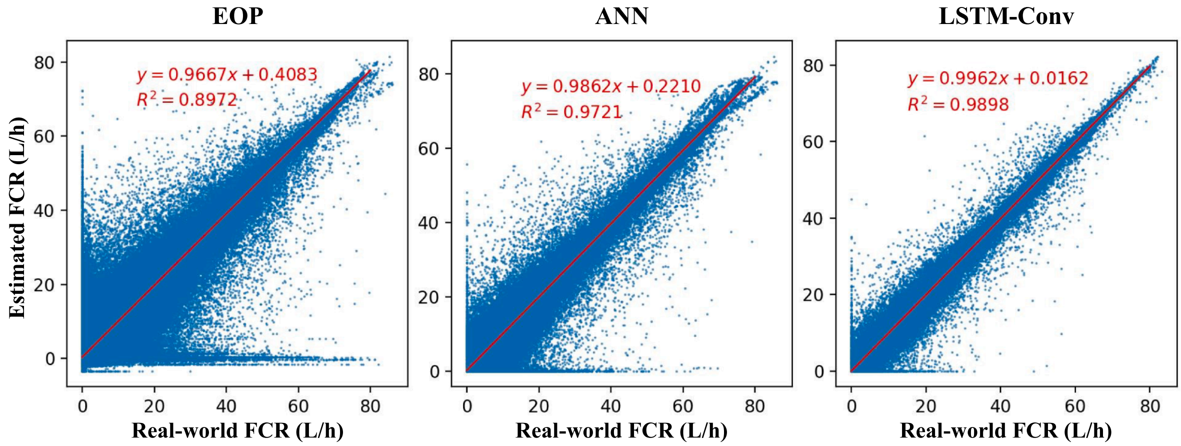


Fig. 8. Performance comparison of EOP, ANN, and LSTM-Conv models in FCR estimation.

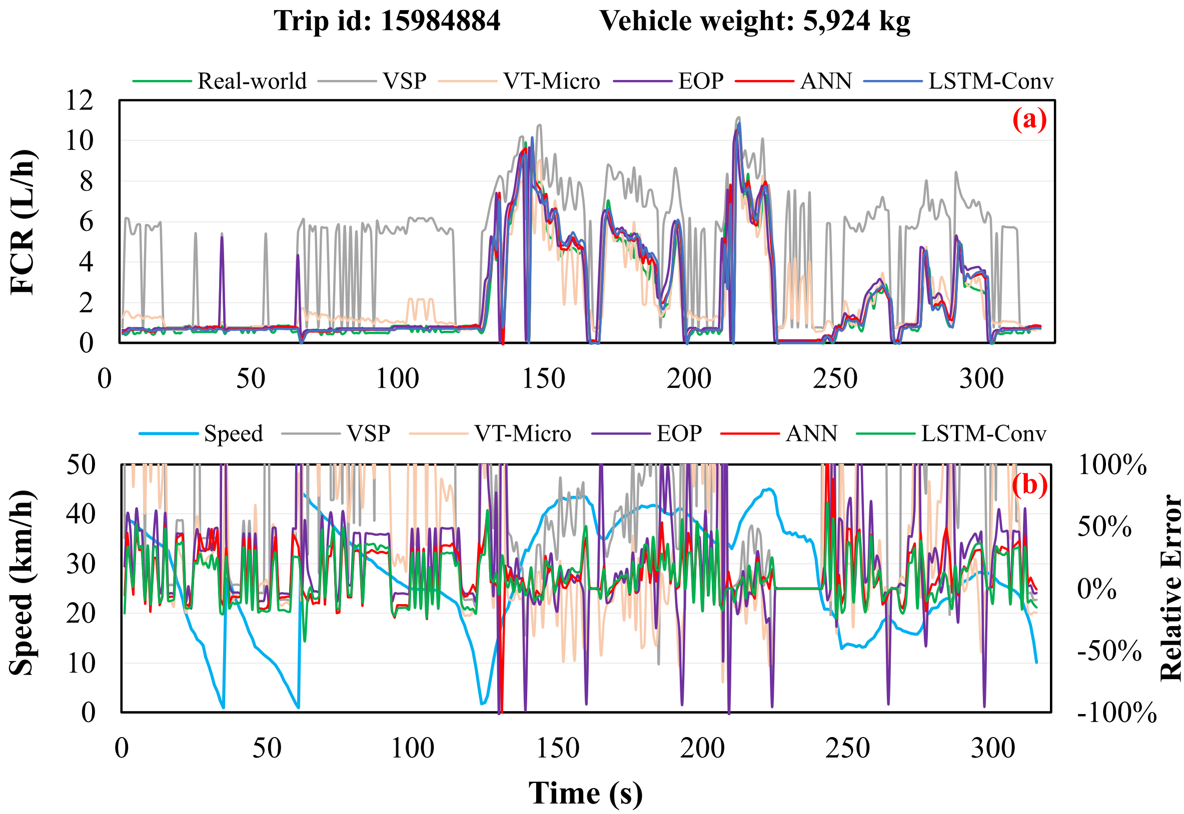


Fig. 9. Analysis results for trip id 15984884 with a vehicle weight of 5,924 kg: FCRs (a), vehicle speed, and relative errors (b).

5. Results and Discussion

5.1. Impact of vehicle weight on fuel consumption

To investigate the impact of vehicle weight on fuel consumption, this research initially analyzed and compared the average FCR across various vehicle weights under standardized operating conditions, with specific attention given to controlling vehicle speed and acceleration. Instantaneous vehicle operating data were chosen from the speed range of 0–120 km/h and acceleration range of −1 to 1 m/s^2. The data were categorized into 24 speed intervals at 5 km/h increments and 40 acceleration intervals at 0.05 m/s^2 increments to create a comprehensive matrix of unique vehicle operating condition intervals. For vehicles with a weight ranging from 0 tons to 5

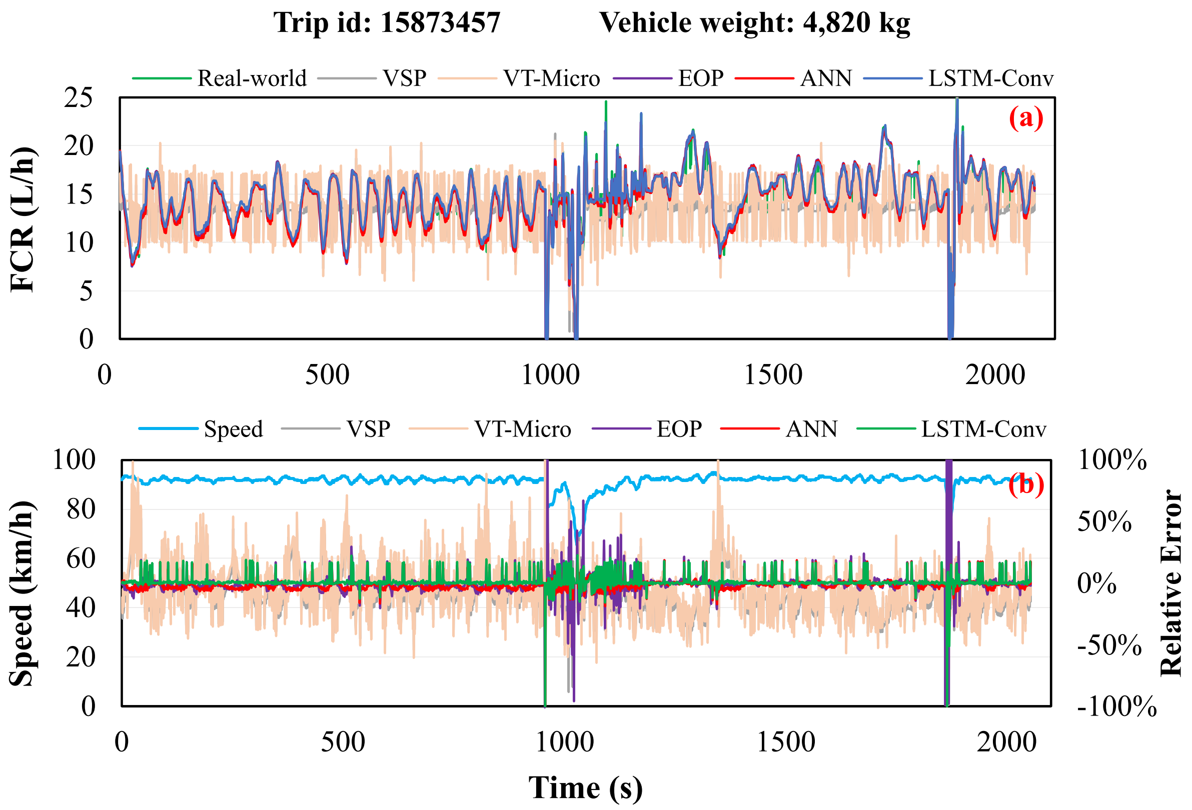


Fig. 10. Analysis results for trip id 15873457 with a vehicle weight of 4,820 kg: FCRs (a), vehicle speed, and relative errors (b).

tons, average FCR values were computed for each interval, establishing the base FCRs as depicted in Fig. 5 (a).

As Fig. 5 (a) depicts, FCR demonstrates significant variations under different operating conditions. During deceleration or at low driving speeds (<10 km/h), FCR remains relatively low, maintaining at approximately 1 L/h. However, FCR undergoes a rapid increase with increasing acceleration. For example, when traveling at a steady 30 km/h with no acceleration, FCR stands at 2.82 L/h. However, it rises to 5.87 L/h with an acceleration of 0.5 m/s^2, representing a 108 % increase, and further increases to 8.67 L/h at 1 m/s^2, marking a 208 % rise. These observations highlight the significant impact of acceleration on FCR, especially at higher speeds and in scenarios involving acceleration. When vehicles traveling from 80 km/h to 95 km/h at an acceleration of 0.2 m/s^2 to 0.4 m/s^2, FCR averages approximately 15 L/h. In contrast, when traveling at 0–15 km/h with an acceleration of −0.4–0.2 m/s^2, FCR averages only 0.9 L/h, demonstrating a significant disparity of approximately 17-fold between the two scenarios. The significant difference in fuel consumption across different speeds and accelerations highlights the crucial impact of these factors on fuel efficiency.

To isolate the impact of vehicle weight on FCR, this research standardized FCR against a base value to derive a ratio that mitigates the variability due to differing operating conditions. Fig. 5 (b) and (c) illustrate these normalized ratios for vehicles with weight ranges of 15–25 tons and 45–55 tons, respectively. An evident correlation exists between the increase in vehicle weight and the rise in FCR. Under similar operating conditions, heavier vehicles exhibited a marked increase in FCR. For example, when traveling at speeds of 20–30 km/h with an acceleration of 0.4–0.6 m/s^2, FCR for vehicles weighing 15–25 tons was 3.9 times higher than that of a 5-ton vehicle, and this ratio further surged to 8.55 times for vehicles weighing 40–55 tons. These findings emphasize the significant impact of vehicle weight on FCR and the importance of considering weight variation in HDT fuel efficiency analyses.

Nonetheless, it is essential to acknowledge that the impact of vehicle weight on FCR does not consistently appear under all operating conditions. During deceleration, the impact of weight on FCR remains relatively minimal, as the normalized ratio hovers around 1 for both 15–25 tons and 45–55 tons, indicating negligible differences. Intriguingly, the observations suggest that even when in an accelerated state, the impact of vehicle weight on FCR at high speed (>70 km/h) is not as prominent as observed at lower speeds. This observed trend may be attributed to the dominance of air resistance over other factors at higher vehicle speeds. The impact of increased vehicle weight on overall fuel consumption becomes less substantial at higher speeds, as air resistance increases proportionally to the square of the vehicle speed, thereby mitigating the relative effect of weight on fuel consumption. Further extensive experiments and in-depth investigations are necessary to substantiate this hypothesis and provide more detailed insights into this phenomenon.

Fig. 5 provides a micro-level visualization of how speed, acceleration, and vehicle weight influence FCR. However, it does not offer a direct comparative analysis of fuel consumption differences between trips with varying weights. To investigate the effect of vehicle weight on trip fuel economy, the trip fuel economies of three representative HDTs under different weight conditions were analyzed, as

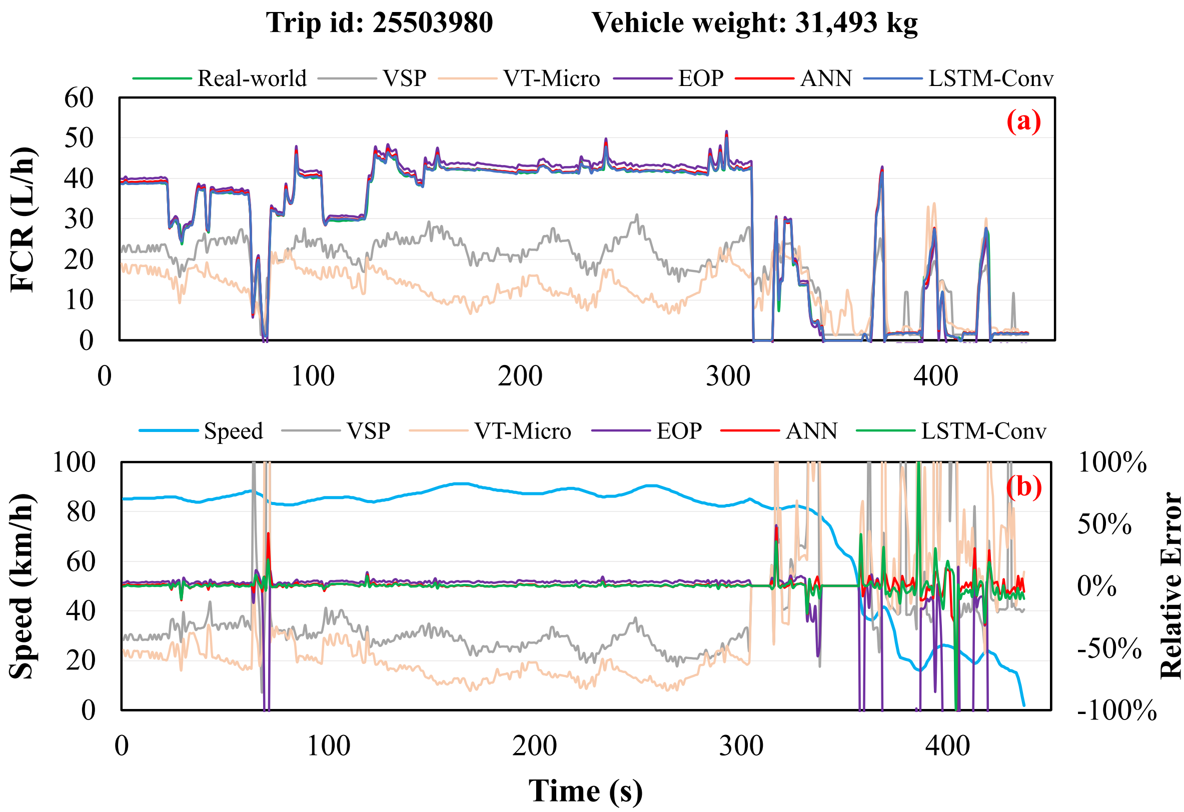


Fig. 11. Analysis results for trip id 25503980 with a vehicle weight of 31,493 kg: FCRs (a), vehicle speed, and relative errors (b).

depicted in Fig. 6 (a–c). The fuel economy increased as the load increased for all three HDTs. For instance, truck 1 exhibited a fuel economy of 16.41 L/100 km when carrying a 10-ton load, but this figure rose to 26.95 L/100 km when the load increased to 25 tons, indicating a substantial 64 % rise in fuel consumption as a result of a 15-ton increase in load. Fig. 6 (d-e) further illustrates the correlation between fuel economies and vehicle weights across all trips. While the fuel economy of a specific trip is closely associated with its average travel speed, which has not been rigorously controlled in this study, an overall positive correlation was identified between fuel economy and vehicle weight. Across all test vehicles, the trip fuel economy is concentrated at approximately 10 L/100 km when the weight falls between 0 and 5 tons, gradually dropping to 60 L/100 km as the weight progressively escalates to 60–65 tons.

In conclusion, vehicle weight has a significant impact on both the micro-level FCR and the macro-level trip fuel economy. Neglecting variations in weight, particularly in HDTs, may introduce potential uncertainties and inaccuracies in fuel consumption estimations. The integration of real-time vehicle weight data into vehicular energy consumption and emissions modeling is imperative to guarantee precision and dependability.

5.2. Model performance on FCR estimation

The comparative evaluations of VSP, VT-Micro, EOP, ANN, and LSTM-Conv models on FCR and trip fuel economy estimation in HDTs are detailed in Table 4, along with further visual representations in Fig. 7 and Fig. 8. It is important to note that all models were trained and calibrated on the same training dataset, and subsequently tested on the same test dataset, yet the sample sizes varied due to specific model requirements. The VSP, VT-Micro, ANN, and EOP models predict individual data points, while the LSTM-Conv model needs 30-second continuous sequences. Besides, tests for the VSP and VT-Micro models were limited to vehicle types with a satisfactory fit, ensuring accuracy in their predictions. The analysis reveals the limitations of the VSP model within the dataset of this study, as evidenced by a MAPE of 182.45 %. This restricted performance can be attributed to the dataset's focus on HDTs, which experience frequent and substantial weight fluctuations ranging from 5 tons to 50 tons. The VSP model, estimating FCR based solely on speed and acceleration, does not incorporate real-world actual vehicle weight information, which makes it fail to account for the crucial impact of vehicle weight on FCR, thereby resulting in inaccurate predictions.

The VT-Micro model, which incorporates complex interactions through high-order combinations of speed and acceleration, performed better than the VSP model. However, it still demonstrated a considerable MAPE of 103.82 % due to the lack of direct vehicle weight information. The EOP model, which directly incorporates engine torque and speed to characterize engine operating conditions, notably decreased MAPE to 50.58 %, demonstrating enhanced performance compared to the VSP and the VT-Micro models.

In contrast, deep learning models leverage an extensive range of feature sets (comprising 17 fields) as inputs, leading to

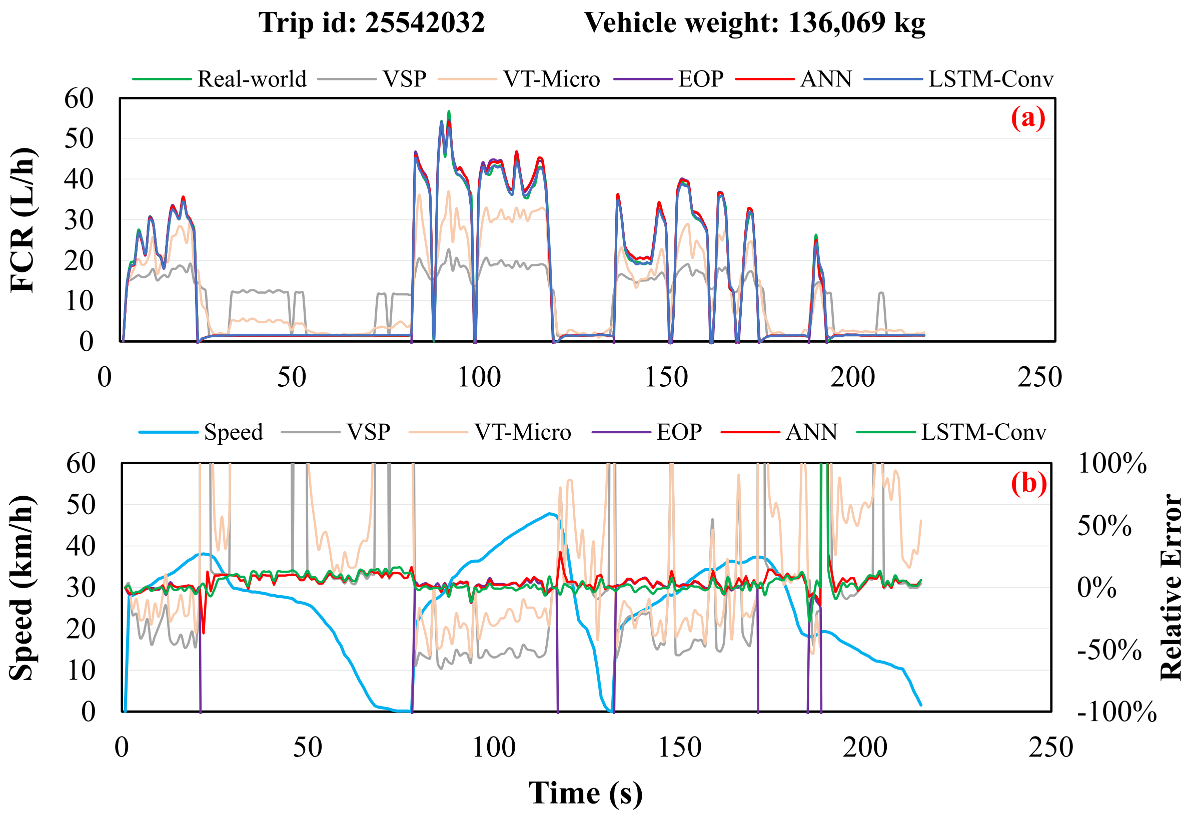


Fig. 12. Analysis results for trip id 2554203 with a vehicle weight of 136,069 kg: FCRs (a), vehicle speed, and relative errors (b).

significantly improved estimation outcomes. The ANN model achieved a MAPE of 15.17 %. The LSTM-Conv model, which is designed to capture both spatial and temporal features of the fuel impact factors, yields a MAPE of 9.81 %. Meanwhile, the LSTM-Conv model maintained a noteworthy MAPE of 10.74 % even in the absence of explicit vehicle weight data, suggesting its potential to infer weight-related influences on fuel consumption. In summary, thanks to the advanced feature extraction capability and the integration of a comprehensive dataset encompassing a diverse range of fuel impact factors, the developed LSTM-Conve model demonstrates improved accuracy in FCR estimation.

As highlighted in Fig. 8, the analysis of prediction errors indicates that errors become more pronounced as real-world or estimated FCR values approach zero. These data points may correspond to abnormalities that have not been eliminated from the dataset. To maintain data consistency, a cautious approach was employed for data quality control, in which only conspicuous outliers characterized by FCR values less than 0 L/h or greater than 100 L/h were excluded from the analysis. As a result, potentially abnormal data points within the dataset may contribute to high prediction errors, which necessitates additional scrutiny and refinement in subsequent analyses.

The model performances with varying vehicle speeds for five representative trips with different weights are presented in Figs. 9–13. All models generally show reduced relative errors when operating at higher speeds and under stable driving conditions. However, their precision decreases with variations in speed. In particular, the VSP and VT-Micro models show relative errors that exceed 100 % at lower speeds (10–50 km/h), as depicted in Fig. 9.

Furthermore, the inaccuracies are exacerbated by the increased weight of the vehicle. The trips represented in Fig. 9 and Fig. 10 involve relatively light vehicles, approximately 5 tons, where the models' performance is marginally better. In contrast, heavier vehicles, such as the 31-ton vehicle depicted in Fig. 11, lead to a notable increase in prediction error, primarily characterized by underestimation in the VSP and VT-Micro models. This tendency to underestimate FCR becomes more pronounced as vehicle weights increase. As illustrated in Fig. 12 and Fig. 13, the VSP and VT-Micro models consistently underestimate real-world FCR by approximately 50 % while capturing the overall fuel consumption patterns.

Fig. 14 illustrates the cumulative fuel consumption curves for the five trips, clearly depicting the trends in model performance relative to vehicle weight. During trips with the vehicle operating at a low load of approximately 5 tons, the VSP and VT-Micro models tend to generate higher estimated fuel consumption values than real-world values. On the contrary, these two models tend to underestimate fuel consumption when dealing with heavier vehicles, particularly those exceeding 30 tons. This underestimation observed at higher weights suggests that the VSP and VT-Micro models might not fully consider the increased fuel demands associated with heavier loads. This indicates a requirement for model adjustments to accurately represent fuel consumption across different weight scenarios.

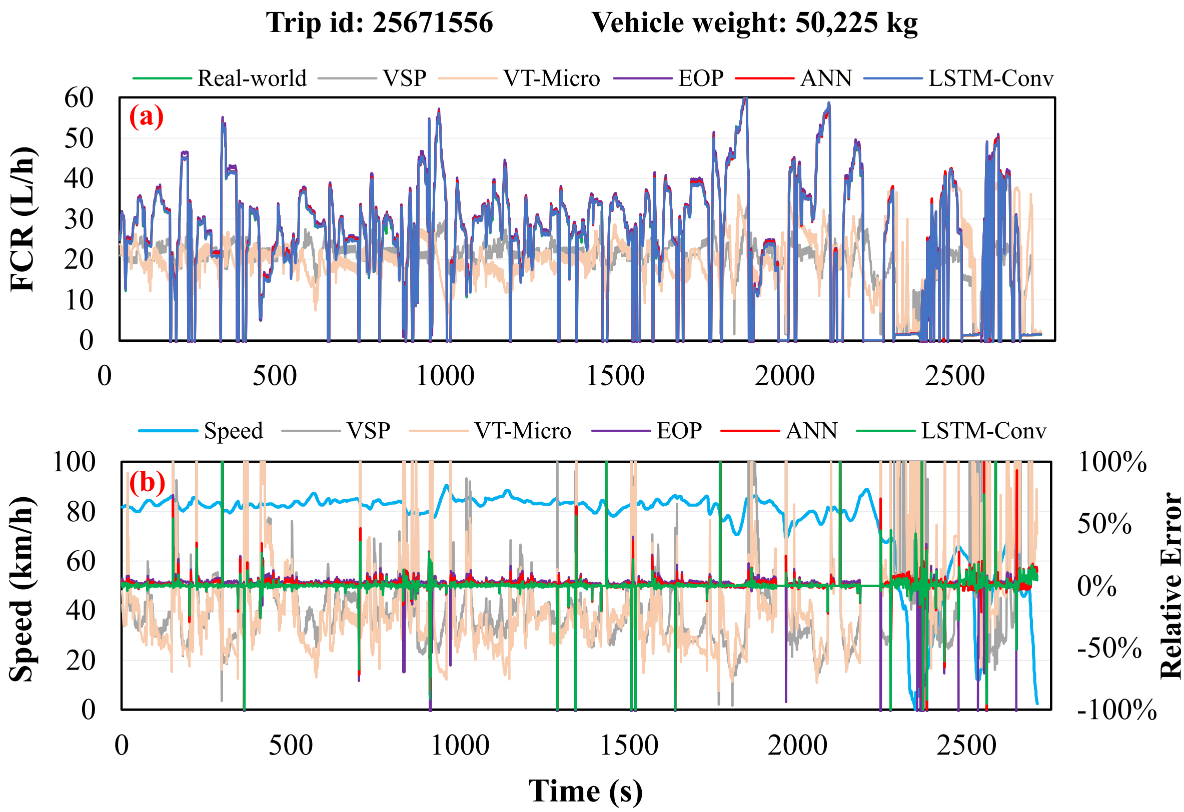


Fig. 13. Analysis results for trip id 25671556 with a vehicle weight of 50,225 kg: FCRs (a), vehicle speed, and relative errors (b).

Fig. 15 and Fig. 16 provide a comparative analysis of the five models' performance for FCR estimation across various speed and acceleration bins. In Fig. 15, the VSP and VT-Micro models demonstrate an increased MAPE at lower speeds, which decreases as the speed increases. Conversely, the EOP model presents a lower level of variability but still exhibits a significant MAPE across the range of speeds. The ANN and LSTM-Conv models stand out for their lower MAPE, indicating a more robust predictive capability. Fig. 16 further reveals that both the VSP and VT-Micro models encounter challenges in maintaining accuracy during acceleration changes, with the VSP model showing particularly high levels of inaccuracy at lower accelerations. The EOP model shows an error increase with higher accelerations, whereas the ANN and LSTM-Conv models consistently exhibit relatively lower MAPEs across all accelerations, indicating their sophisticated handling of dynamic driving conditions. The aforementioned figures highlight the superior performance of deep learning models in capturing the intricacies of fuel consumption patterns, with the LSTM-Conv model consistently demonstrating exceptional accuracy in both speed and acceleration domains.

5.3. Model performance on trip fuel economy estimation

This study evaluated the model's performance in predicting trip fuel consumption by aggregating the predicted second-by-second FCR for each trip and comparing these with the real-world trip fuel consumption values. Despite the VSP and VT-Micro models' poor FCR prediction for HDTs, we still include their trip fuel economy estimation results since they are important baseline models with high simplicity and widespread application. As shown in Table 4 and Fig. 17, the cumulative approach results in a notable improvement in prediction accuracy compared to instantaneous FCR estimations. This improvement is attributed to the mitigating effect of data aggregation throughout the trip duration. Fig. 17 showcases a strong linear correlation between estimated and real-world fuel consumption for all models. The LSTM-Conv and ANN models demonstrate the highest congruence, as evidenced by their regression line slopes and R^2 values approaching 1. The VSP model achieves a MAPE of 28.49 % for trip fuel consumption prediction. In comparison, the VT-Micro, EOP, ANN, and LSTM-Conv models demonstrate MAPEs of 21.75 %, 5.49 %, 2.31 %, and 1.49 %, respectively, with the LSTM-Conv model yielding the most accurate predictions.

Further analysis, as shown in Fig. 18, reveals a correlation between trip prediction errors and vehicle weights. The boxplots illustrate systematic biases in the VSP, VT-Micro, and EOP models, showing a tendency to overestimate fuel consumption for lighter vehicles and underestimate it for heavier ones. This phenomenon is likely attributable to the absence of weight integration in the models, leading to predictions converging toward the historical average fuel consumption observed across diverse load conditions. In contrast, the ANN and LSTM-Conv models demonstrate consistent accuracy regardless of vehicle weight variations, as evidenced by their median errors converging around zero throughout the entire weight range, highlighting their robustness and strong abilities to

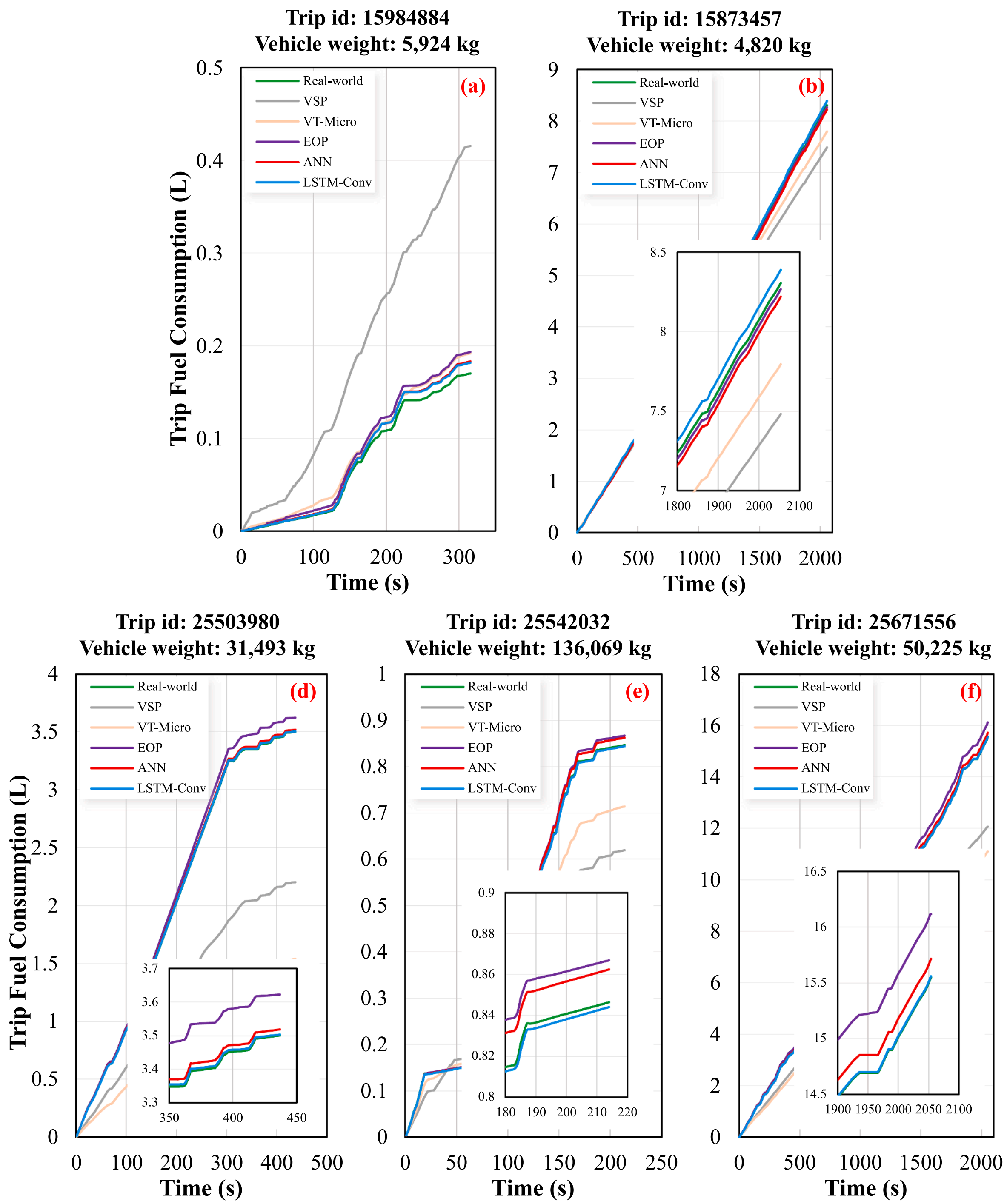


Fig. 14. Trip fuel consumption for five sample trips with different vehicle weights.

capture weight effects within their predictive frameworks.

Though the VSP and VT-Micro models are appreciated for their simplicity and interpretability, their precision is limited by the absence of direct vehicle weight input, especially in applications requiring precise FCR estimation, such as eco-driving for HDTs. Deep learning models address this gap by providing high-precision estimates through the adept handling of comprehensive fuel impact factors, despite the expense of reduced transparency.

However, the practical applicability of the VSP and VT-Micro models (or other vehicle dynamic-based models) remains significant, particularly in situations where data is scarce, and precision is not crucial, such as in macroscopic assessments of fuel consumption

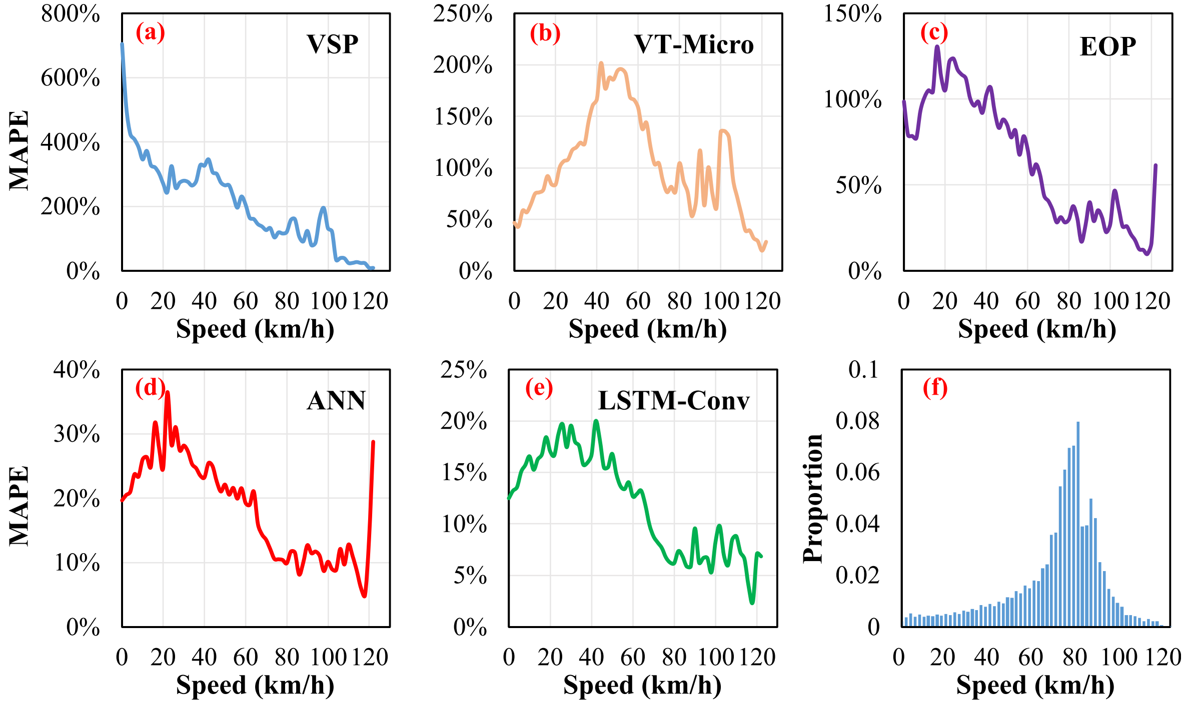


Fig. 15. Comparative analysis of MAPEs versus instantaneous speeds for five proposed models (a–e) and speed distribution of training data (f).

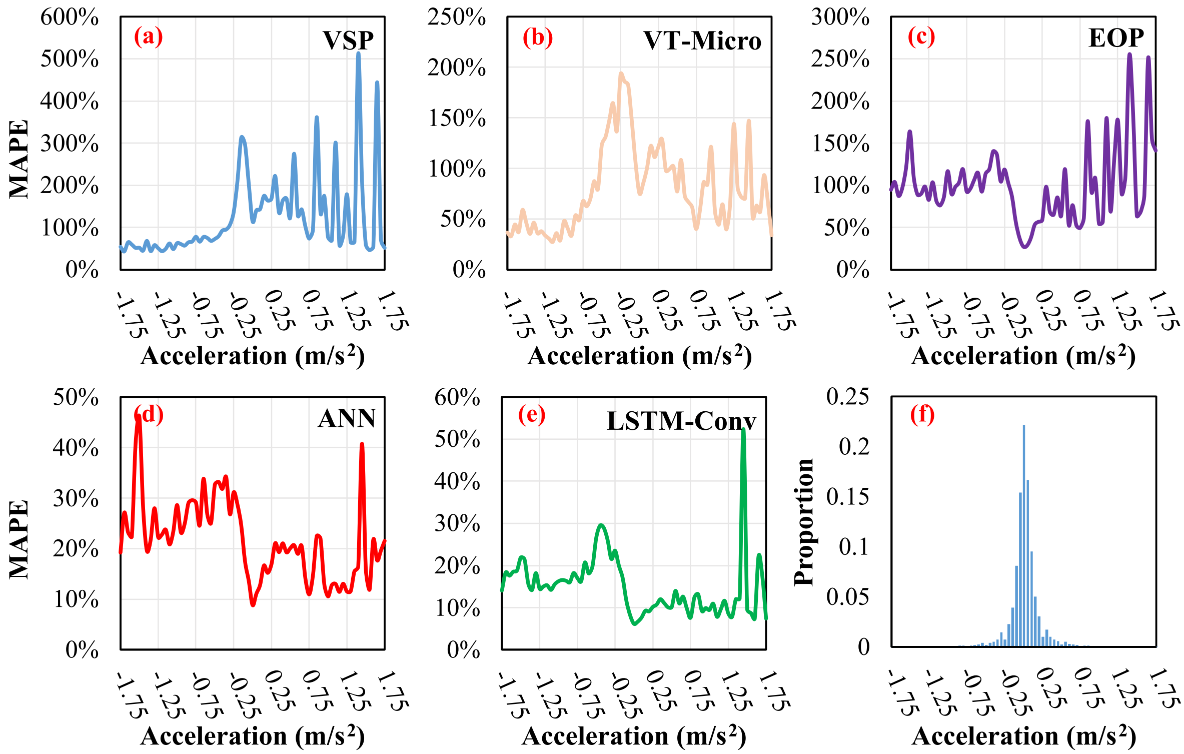


Fig. 16. Comparative analysis of MAPEs versus instantaneous accelerations for five proposed models (a–e) and acceleration distribution of training data (f).

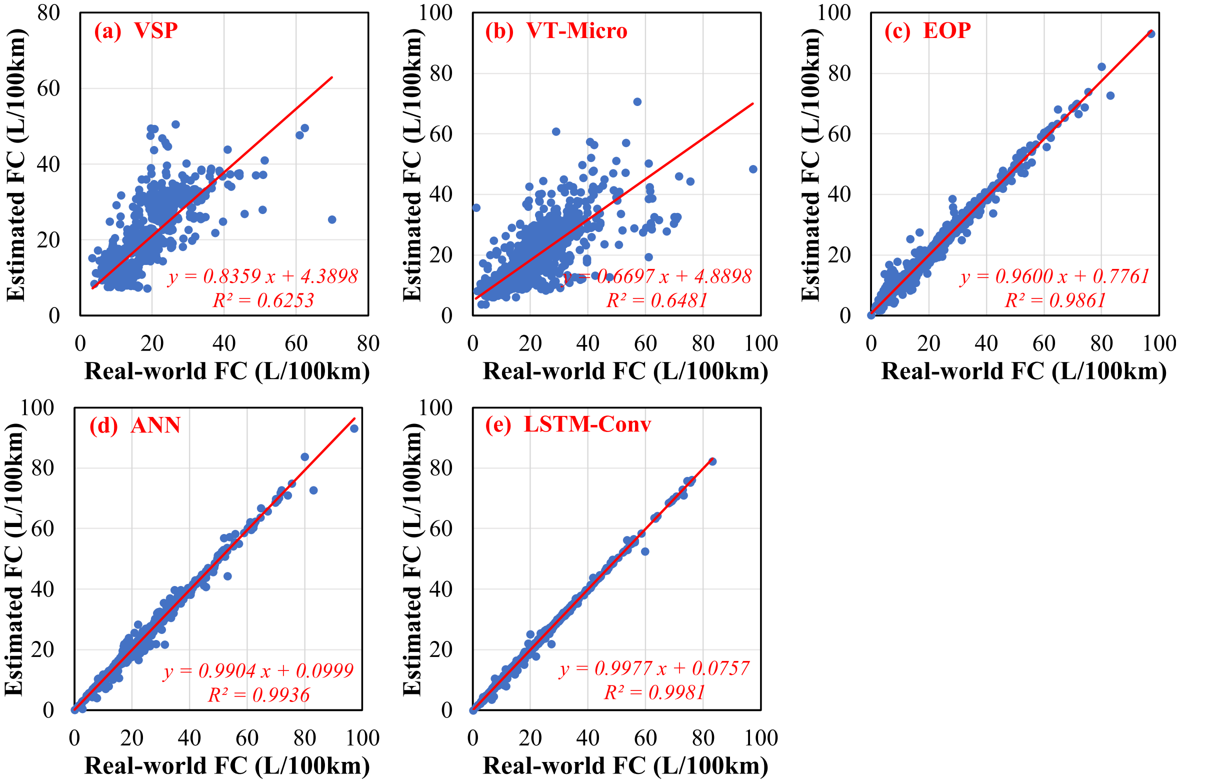


Fig. 17. Comparative analysis of estimated trip fuel consumption versus real-world measurements for VSP, VT-Micro, EOP, ANN, and LSTM-Conv models.

across road segments or entire trips. The results of this study emphasize the importance of integrating real-world vehicle weight into the VSP and VT-Micro models to enhance their accuracy. This integration positions the VSP and VT-Micro models as more comprehensive tools for transportation research, bridging the gap between model interpretability and precision in fuel consumption modeling.

6. Conclusion

Insufficient consideration of vehicle weight fluctuations in fuel consumption estimations introduces potential inaccuracies and uncertainties. This study conducted a detailed analysis of the impact of vehicle weight on FCR and trip fuel economy from both micro- and macro-perspectives based on extensive filed operating data collected from 162 HDTs' real-world driving conditions. Fuel consumption models utilizing deep learning algorithms were developed, and the effectiveness of the VSP, VT-Micro model, and the proposed EOP, ANN, and LSTM-Conv models for FCR and trip fuel consumption estimation were evaluated. The following conclusions can be summarized:

1. There is a significant but uneven impact of vehicle weight on FCR across different operating conditions. Under operating conditions at speeds of 20–30 km/h and accelerations of 0.4–0.6 m/s^2, FCR increases by 290 % and 755 % for vehicle weight ranges of 15–25 tons and 45–55 tons, respectively, compared to the base FCR observed at weights of 5 tons. However, this impact was less pronounced during deceleration or at higher speeds.
2. A clear positive correlation exists between the average trip fuel economy and vehicle weight. The fuel economy increased from approximately 10 L/100 km for a 5-ton vehicle to 60 L/100 km for a 60-ton vehicle
3. The advanced deep learning models, specifically ANN and LSTM-Conv models, demonstrate superior performance in estimating fuel consumption compared to the VSP, VT-Micro, and EOP models. The LSTM-Conv model achieves MAPEs of 9.81 % for FCR and 1.49 % for trip fuel consumption. The LSTM-Conv model exhibits the ability to implicitly infer the weight-related impacts from continuous vehicle operating data. Despite the absence of explicit input for vehicle weight in the model, the LSTM-Conv model still achieves MAPEs of 10.74 % and 1.93 % for FCR and trip fuel consumption, respectively.
4. In comparison to the traditional physical models (VSP, VT-Micro, EOP), the deep learning models (ANN and LSTM-Conv) demonstrate improved stability across different speeds, accelerations, and vehicle weights. This contrasts with the tendency of conventional models to overestimate fuel consumption at low loads and underestimate it at high loads.

These findings emphasize the importance of considering the complex impact of vehicle weight on fuel consumption. Conventional

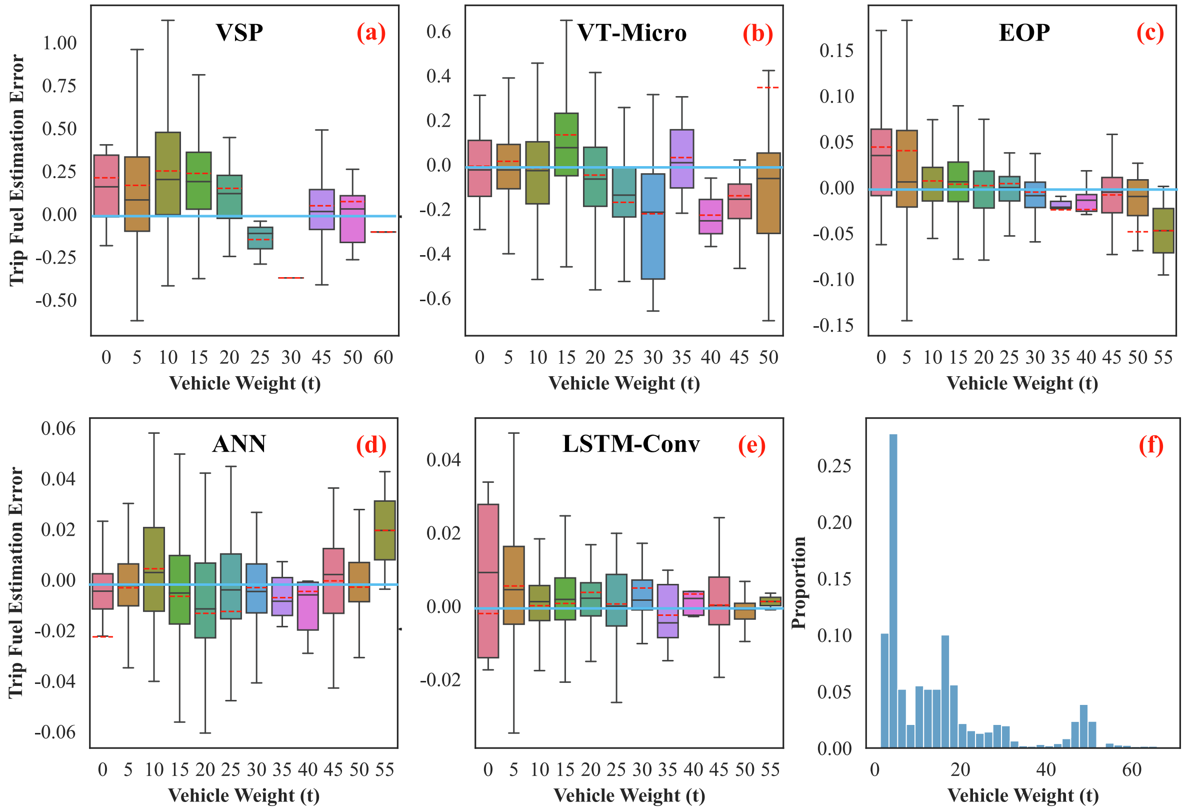


Fig. 18. Comparative analysis of trip fuel consumption estimation error versus vehicle weight for five proposed models (a–e) and weight distribution of training data (f).

models, which typically depend on speed and acceleration, lack direct integration of vehicle weight information. In contrast, deep learning models have the capability to identify complex relationships between various operating conditions and fuel consumption, thereby leading to more precise predictions. The improved accuracy and reliability of these technologies play a crucial role in the formulation of effective eco-driving strategies and fuel-saving technologies, contributing to reduced environmental impact and operational expenses.

In terms of trip-wise analysis, however, the accuracy gap between conventional and deep learning models was less significant, with all models achieving R^2 values above 0.60 and MAPEs below 30 %. This finding suggests that although deep learning models offer much higher precision in instantaneous FCR estimation, conventional models are still viable for broader, macroscopic assessments where high-accuracy FCR estimation is not a priority, given their simplicity and interpretability. Achieving a balance between model complexity and interpretability is crucial, especially in applications where understanding the drivers of fuel consumption is necessary.

Future research will expand to incorporate more diverse data on factors influencing fuel consumption, such as road grade and weather conditions (Hamdar et al., 2016; He et al., 2022; Liu et al., 2019; Liu et al., 2023b; Wang et al., 2022b). Additionally, there will be a comprehensive evaluation of model performance across various traffic conditions, driving scenarios, and vehicle types, coupled with an in-depth examination of error terms to refine the models for higher accuracy and reliability. Given the potential limitations of detailed OBD data, future work will also investigate the overall robustness and performance of the LSTM-Conv model under sparse data conditions. Furthermore, it is important to recognize the crucial role of traditional models, and efforts will be made to improve these models through a detailed, in-depth fuel consumption causality analysis.

In summary, this study contributes to a more comprehensive understanding of fuel consumption dynamics in HDTs and emphasizes the importance of integrating vehicle weight into fuel consumption modeling. This integration is crucial for the development of eco-driving and eco-routing strategies, the optimization of fuel consumption, and the support of broader decarbonization initiatives.

CRediT authorship contribution statement

Pengfei Fan: Writing – review & editing, Writing – original draft, Visualization, Software, Methodology, Investigation, Funding acquisition, Formal analysis, Data curation, Conceptualization. **Guohua Song:** Writing – review & editing, Writing – original draft, Resources, Project administration, Methodology, Funding acquisition, Data curation, Conceptualization. **Zhiqiang Zhai:** Writing – review & editing, Writing – original draft, Methodology, Investigation, Conceptualization. **Yizheng Wu:** Writing – review & editing, Writing – original draft, Methodology, Funding acquisition, Conceptualization. **Lei Yu:** Writing – review & editing, Resources, Project administration, Funding acquisition.

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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