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Deep learning long short-term memory methods for instantaneous fuel consumption prediction: Experimental study and comparison of modeling strategies

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ABSTRACT

This paper presents an empirical study on the prediction of the instantaneous fuel consumption of public transport buses using LSTM type recurrent neural networks. The analyses were conducted on selected repetitive Sort 2 driving cycles. This allowed for stable test conditions and control of data variability. For the analyses, valid measurements including vehicle speed, accelerator pedal position (APP) and instantaneous fuel consumption (l/h) were used. Five LSTM modelling strategies were developed and compared: a baseline model, an in-depth model with dropout, an advanced model with callbacks, a model with a special weighted loss function for idling periods and a FuelNet model for fuel consumption prediction. The results indicate high prediction performance (MAE, RMSE, R^2) and the potential for practical implementation of the model in fleet management systems.

Keywords: prediction, fuel consumption, bus, LSTM, neural network.

INTRODUCTION

In the perspective of the decarbonisation of the public transport sector, the EU is aiming for zero emissions in urban areas by 2040. As a result, transport companies are replacing their vehicle fleets with green energy vehicles. However, the operative-TCO value for vehicles powered by green HFCE (hydrogen fuel cell electric) is 23–37% higher compared to vehicles powered by diesel, CNG (compressed natural gas) or grey-HFCE [1]. This makes the primary energy source of the newly sold city buses still diesel in 2022 about 67% [2] and in 2024 about 61–63% [3, 4]. Despite the declining trend, more than 60% of operators choose to purchase a new diesel-powered vehicle.

One of the important components of the total cost of owning and operating a means of transport (TCO) is the consumption of materials, fuel and energy. A cost analysis in car transport companies has shown that the cost of fuel accounts for 15–20% of TCO [5], while in public transport for city buses equipped with a CI engine it is as much as 25–30% [6]. For this reason, research work is being carried out on the process of converting the chemical energy contained in the fuel into mechanical and electrical energy [7–11]. Of course, this is not the only factor that contributes to engine research and development. An important aspect related to engine operation is the emission of toxic exhaust components such as nitrogen oxides, hydrocarbons, carbon monoxide or particulate matter and carbon dioxide emissions [12–14].

There are different methods used to reduce fuel consumption. One of these is to replace the electricity generated from fuel by using several alternators on board the vehicle. For this purpose, photovoltaic panels [15, 16] or vehicle kinetic energy recuperation systems [17, 18] are mounted on the roof of the vehicle. Another method to minimise energy consumption is to optimise fuel costs and sustainability through the use of monitoring and predictive tools for fuel consumption in public transport. Current traditional regression models often do not take into account the complexity of urban traffic and the variability of vehicle signals.

The literature analysis shows the extensive use of classical modelling methods such as regression, ARIMA (autoregressive integrated moving average) or MLP networks for data analysis and forecasting. While regression assumes a linear relationship between variables, ARIMA models forecast time series based on data collected at regular intervals. In contrast, MLP networks (MultiLayer Perceptrons) are a type of artificial neural network that can model very complex non-linear data relationships. Although they are more universal and can be used for both forecasting and classification and often handle difficult patterns better than statistical methods they are more difficult to use for interpretation.

Bus fleet management aimed at minimizing operational and environmental costs requires the implementation of strategies that optimize the use of vehicles with different drives [19]. At the same time, the use of machine learning methods to predict energy consumption allows for more accurate forecasting of energy demand based on actual operating conditions, which supports decision-making in the field of planning and optimization of fleet operation [20].

Traditional statistical and analytical models such as regression are used to identify critical parameters (driving style, landscape, road conditions, etc.) affecting fuel consumption of specific vehicle types. The paper [21] presents a methodology for determining a statistical model of fuel consumption based on an analysis of the relevance of driving parameters. A fleet of trucks from the commercial freight transport sector was studied. It was shown that the number of vehicle stops and emergency braking had the least impact on average fuel consumption. In contrast, a study [22] showed that in passenger vehicle transport, the driver's driving style was significant for instantaneous and average fuel consumption values.

For modelling fuel consumption, artificial neural networks are also used. Compared to regression models, they have less stringent input data requirements and can analyse more complex non-linear relationships without being explicit [23, 25, 26]. Nevertheless, in both cases, similar approx. 3% differences in calculated and actual average fuel consumption were obtained [21, 23].

The researchers are aiming to improve the accuracy of modelling methods. There is growing interest in the use of LSTMs for time series prediction, due to their ability to analyse long-term sequential relationships [26–32]. For fuel consumption modelling, researchers have mainly focused on the topic of energy consumption prediction in marine transport. In the study [27], the authors focus on the optimisation of the LSTM model using a genetic algorithm for VLOC (very large ore carrier) vessels. In order to develop a digital twin of the fuel consumption of a marine vessel, in this case the R/V Gunnerus research vessel, correlation and sensitivity analysis was used to select the input parameters and optimise the configuration of the LSTM model. Real operating data from the R/V Gunnerus was used to verify the model [28].

The research shows the superiority of predictive learning models compared to traditional energy consumption models based on BP, SVR and ARIMA [27, 30]. The use of the genetic algorithm (GA) optimisation method optimises the number of network layers, number of neurons and batch/size (Batch_size) of the LSTM network, resulting in a minimised prediction error for operational ship energy efficiency of 0.29% [30]. As a result, these models are very effective in predicting the fuel consumption of vessels under different voyage conditions, which is useful in optimising and improving their energy efficiency.

Although traffic conditions, engine load dynamics, and environmental conditions are different in water and road transport, the application of the LSTM model in predicting the fuel consumption of buses used in urban public transport can contribute to increasing their energy efficiency, reducing costs, and minimising the environmental impact of land transport.

The objective of this paper is to develop, implement and compare the performance of five variants of LSTM models for the prediction of instantaneous fuel consumption in urban buses based on real data. The choice of repetitive driving cycles (Sort 2) was made deliberately to ensure control over the nature of the data and to reduce the impact of uncontrolled environmental factors on the results. This enabled a more precise assessment of model performance and analysis of the impact of the network architecture on the quality of the prediction under stable driving conditions.

DATA ACQUISITION AND PRE-PROCESSING

The investigation was carried out under road conditions at the former military airport in Biała Podlaska (Poland). The facility offered favourable conditions with a 3.300-metre-long main runway and a 2.700-metre-long reserve runway (Figure 1). The airport was regularly used for road tests of vehicles and motorsport events until 2020. Both a section of the main runway and part of the service lanes were used for the tests. This infrastructure enabled repeated driving cycles to be carried out, additionally allowing the engine load to be altered by increasing the alternator load.

The object of the study was a city bus, Mercedes Conecto LF (Figure 2), owned by the Municipal Transport Company in Lublin (Poland). It is a 12-metre long, low-floor bus, built from welded closed profiles, which can accommodate a maximum of 94 passengers (26 seated and 68 standing). It is powered by a 6-cylinder OM 926 LA in-line diesel engine, located in the left rear corner of the vehicle. The engine has a capacity of 7.23 dm³ and develops a maximum power of 205 kW (278 hp). The bus complies with the Euro IV emissions standard thanks to BlueTec technology, which uses the injection of AdBlue fluid into the catalytic converter. Transmission from the engine is via a Voith 854.3 4-speed automatic transmission, the main gearbox located in the ZF AV-132 drive bridge, to the vehicle's drive wheels. The bus features an electronically controlled air suspension system, allowing precise control of ride comfort and lowering the platform for easier passenger access.

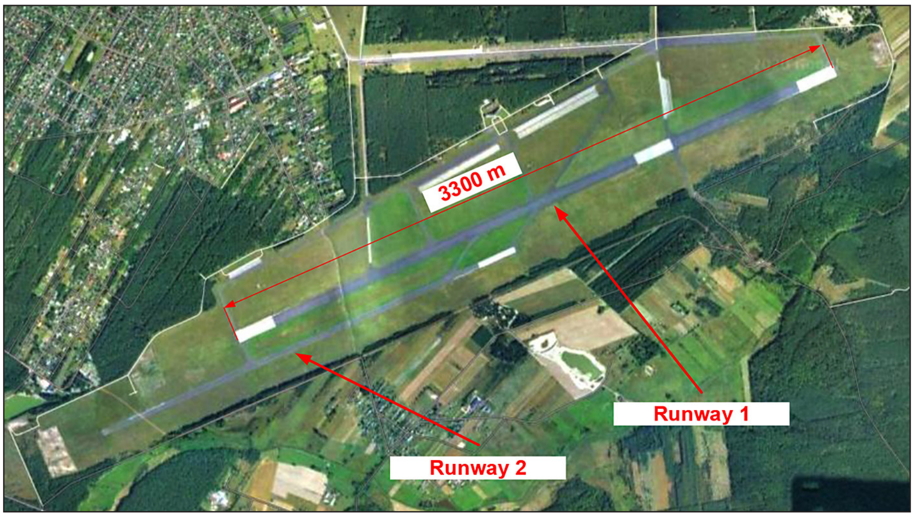

Figure 1. View of runways on the airport [7]

Figure 2. Mercedes Conecto LF city bus [7]

The vehicle was equipped with an on-board data logging system consisting of an NI cRIO-9024 controller running in a real-time operating system, an NI 9862 CAN interface compatible with C-Series enclosures and running in Windows and Real-Time, an NI cRIO-9118 universal measurement card support module and an NI 9871 RS485/RS422 interface with 4 ports, compatible with C-Series enclosures. All modules are integrated in the LabVIEW environment.

Signals recorded included vehicle speed Vr, accelerator lever position APP, instantaneous fuel consumption Ge [dm^3/h], as well as time and basic route data. A schematic of the measurement system is shown in Figure 3.

During the tests, the driver monitored both the target Vt and the current Vr speed on the screen in real time. All measurements were collected in one day, with an ambient temperature of around 2 °C and a southwesterly wind of 7–10 km/h. Precise bus speed measurement, with a resolution of 0.1 km/h. The driving cycle was repeated five times during one run. The results of the measurement are included in Figure 4. The presented time frames show the changes in three operating parameters of the vehicle during the driving test: accelerator pedal position (APP), vehicle speed (V) and fuel consumption (Ge). In the first graph (APP), the sequential variability of the APP is noticeable, with periods of acceleration followed by phases of engine braking or standstill. The middle graph shows the vehicle speed (V), which varies according to the Sort 2 cycle, reaching a maximum of approx. 50 km/h. The recorded data provides valuable for machine learning, enabling modelling and prediction of fuel consumption in real-world urban operation conditions.

The data preparation process included preliminary analysis as well as signal processing. Data corresponding to the repetitive driving cycles of SORT2 (Standardised on–road test) were selected. This made it possible to reduce the influence of random disturbances and to ensure the consistency of the observations. Due to the dynamics of the drive train operating phenomena, the recorded data were sampled at 10 Hz. Channel synchronisation was also verified.

The study is based on an analysis under controlled conditions, using a single vehicle type and the SORT-2 cycle. This approach eliminated disturbing factors and ensured consistent reference data. The aim was to verify the methodology and predictive models in an unambiguous way. The results may serve as a basis for estimating future fuel consumption, similar to the approach applied in the VECTO tool.

During signal processing, input data normalisation was performed using the MinMaxScaler function. The data were then transformed into a fixed-length sequence (time window), defining a short-term history of the vehicle state. A three-dimensional input tensor (time, feature, sample) was created, using vehicle speed (V) and APP as input variables, and instantaneous fuel consumption (l/h) as the output variable.

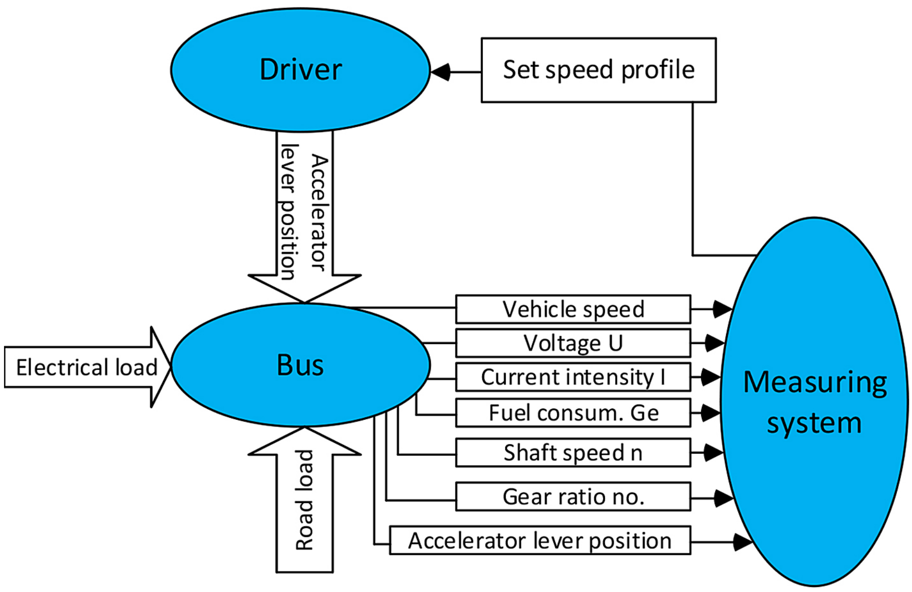

Figure 3. Diagram of the road test measurement system [1]

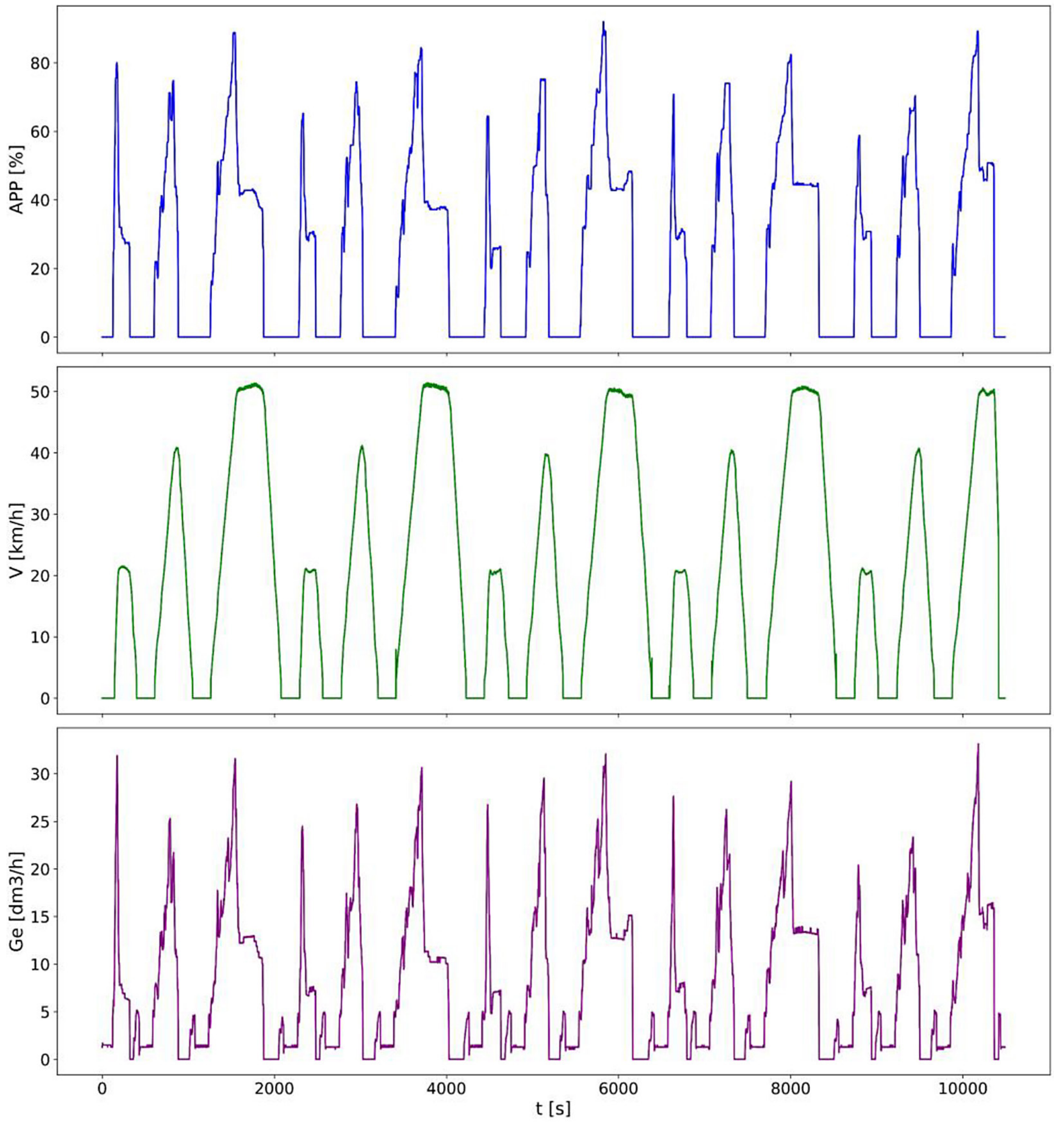

Figure 4. Results of road tests, fuel consumption (Ge), vehicle velocity (V), acceleration pedal position (%)

SCOPE OF THE MODEL STUDY

In order to determine the most effective method for predicting the fuel consumption of a city bus, five different approaches to building models based on neural networks were carried out. Each successive approach incorporated further improvements to the architecture or learning process, in line with the progress of the research and the conclusions of previous analyses. A summary of the modified parameters is included in Table 1, while a broader description is provided in the following table. The description of model is:

- LSTM 1 – the basic single-tier model: the first step used a basic LSTM (long short-term memory) network architecture, with one LSTM layer (64 neurons) and a Dense output layer. The model was taught for 20 epochs on input sequences of 20 samples, using the standard Adam optimisation algorithm and a mean squared error (MSE) type loss function. Input data included vehicle speed and APP signal, and the output variable was instantaneous fuel consumption [l/h].
- LSTM 2 – depth extension and regularisation: the second step involved increasing the complexity of the model by introducing two LSTM layers (with 64 and 32 neurons, respectively) and using Dropout layers (p = 0.2) after each recurrent layer to reduce the risk of overfitting. In addition, the length of the input sequence was extended to 30 samples and the number of epochs was increased to 40. The model was

Table 1. Comparative overview of model

Model	Architecture	Input sequence	Epochs	Dropout	Loss function	Additional features
LSTM 1	LSTM (64) + Dense	20 time steps	20	None	MSE	Baseline model
LSTM 2	LSTM (64) → LSTM (32) + Dense	30 time steps	40	0.2	MSE	Overfitting reduction
LSTM 3	LSTM (128 → 64 → 32) + Dense	40 time steps	Dynamic (Early stopping)	0.3	MSE	He normal init, ReduceLROnPlateau, ModelCheckpoint
LSTM 4	Same as LSTM 3	40 time steps	Dynamic (Early stopping)	0.3	Weighted MSE	Sample weighting for idle mode (< 2 l/h)
FuelNet	MLP (5 Dense layers)	No sequence (flat input)	Dynamic (Early stopping)	0.2	MSE	ReLU activation, classical Feedforward neural network (FFN) architecture

taught on normalised data and the predictions were verified against actual measurements.

- LSTM 3 – automation of the learning process and a deeper network: the third step introduced further automation of the learning process, using EarlyStopping and ReduceLROnPlateau mechanisms to dynamically adjust the number of epochs and the learning rate. The model had an even deeper architecture, with three LSTM layers (128, 64 and 32 neurons) and Dropout layers (p=0.3). The sequence was extended to 40 samples and the batch size was reduced to 16. Initialisation of weights ("he_normal") was also used. The checkpoint model saved the best version of the model based on the loss function.
- LSTM 4 – model with weights for idling: the fourth step was an advanced modification of the third version. Sample weighting was introduced, giving higher weighting to samples corresponding to idling (defined as fuel consumption < 2 l/h). The aim was to increase the accuracy of the prediction of low fuel consumption, which is particularly important for the efficiency of bus fleets. In addition, an in-house loss function was used to allow weights to be passed to the learning algorithm. Other aspects of the model corresponded to the architecture of the third approach.
- FuelNet – a dedicated Feedforward deep neural network architecture: the FuelNet deep feedforward neural network (MLP) model, consistent with the literature, was used as a benchmark for comparison with LSTM architectures. FuelNet consists of five fully connected layers, with a decreasing number of neurons, ReLU-type activation functions and Dropout (p = 0.2) between layers. The model was trained identically to the LSTM models, using the same input and output data. The aim was to verify whether sequential architectures (LSTM) significantly outperform classical models in the fuel consumption prediction task.

MODEL VALIDATION AND RESULTS ANALYSIS

In the presented approach to modelling the instantaneous fuel consumption of a vehicle, the strategy of training the model on the full reference data set (base file) was adopted. The assessment of the prediction quality was carried out on a separate test file, not participating in the training process. This configuration corresponds to a typical division into a training set and a test set, with the difference that instead of a random or sequential division of one data set, a division of data from different measurement sessions is used. The risk of data leakage between training and evaluation phases has been eliminated. Consequently, the calculated error metrics (MAE, RMSE, R^2) can be considered reliable and resilient to overfitting. Figures 5a-5e show the results of the model validation on additional data that were also obtained during the Sort 2 test run, but with an increased value of engine load by increasing the electrical power consumed by the electrical devices in the vehicle. The red line represents the experimental values, while the blue line represents the values predicted by the model. The R^2 (Coefficient of determination) value shown in the Figures 5a-5e refers to the goodness-of-fit of a linear regression applied to a 35% random subset of the predicted vs. actual values. It does not represent the true performance of the model, which is evaluated using the full dataset and reported separately in the metrics summary.

Figures 5a–e show the results of five fuel consumption prediction models, comprising four LSTM-based architectures (LSTM1-LSTM4) and one MLP-type model (FuelNet). The evaluation of each model was based on two types of visualisation: a comparison of the time course of measured and predicted values of instantaneous fuel consumption (graphs on the left) and (2) a scatterplot of actual and predicted values with fitted linear regression and coefficient of determination R^2 (graphs on the right).

The LSTM 1 sequential baseline model (Figure 5a) provides a baseline for subsequent modifications. The time course shown reflects the main trends, but deviations are evident in the areas of fast changes and for idle speed. A moderate scatter of points relative to the ideal line is observed in the scatter plot. The R^2 value is 0.977, indicating correct, although limited, predictive accuracy.

The LSTM2 model with greater depth and regularisation (Figure 5b) was extended with a second LSTM layer and dropout was applied. This has improved the model's ability to analyse complex temporal relationships. Predictions are closer to the actual values, especially in the transition phases. The scatter plot shows a higher concentration of points near the ideal line and a higher $R^2 = 0.9872$.

The LSTM 3 model extended with dynamic learning and deep architecture (Figure 5c) using three layers of LSTM and the EarlyStopping and ReduceLROnPlateau mechanisms. This has enabled a better fit to the data, especially in the areas of low consumption and longer constant driving passages. The R^2 value reaches 0.9907 and the predictions show minimal deviation from measured values.

The LSTM 4 model with weights for idling (Figure 6d) is an extension of the third version with a system of weights assigned to idling trials (< 2 l/h). This has made it possible to increase the precision of the predictions in the sensitive areas of low consumption relevant to urban fleets. Predictions remain highly consistent with the measurement, with the R^2 value increasing to 0.992 – the highest of all models.

The FuelNet model (Figure 5e) represents a classic MLP-type network with a five-layer Dense structure. The model correctly reproduces the fuel consumption trend, but shows limited sensitivity to dynamic changes and abrupt transitions. In spite of this, a high $R^2 = 0.992$ was obtained. This indicates good prediction of steady-state values, with less effectiveness under variable conditions.

All the models used show acceptable predictive capability for instantaneous fuel consumption. The accuracy of the prediction increases with the depth of the architecture and the application of regularisation techniques. The sequential models (LSTM3-LSTM4) show a clear advantage over the classical MLP model (FuelNet) in terms of dynamic representation and precision at low consumption. The highest performance is achieved by the LSTM4 model, due to the use of sample weighting in the idling range. However, it should be mentioned that the use of the FuelNet model is more efficient to some extent, as it will require fewer hardware resources for future fuel consumption forecasting.

Figure 6 shows a comparison of the predictive accuracy of the five regression models considered. Four classic quality assessment metrics were used: mean absolute error (MAE), mean squared error (MSE), root of mean squared error (RMSE) and coefficient of determination (R^2). The metric values were determined based on validation data that the model did not see during training. The obtained values of MAE, MSE and RMSE indicate a small prediction error, while a high R^2 indicates a good ability of the model to represent the variance of real data.

The best results were obtained by the LSTM2, LSTM3 and LSTM4 models, which achieved low errors (MAE ≈ 0.47–0.49) and high R^2 values (≥ 0.986), indicating high prediction precision. The FuelNet model, despite a high R^2 (0.938), generated significantly larger MAE and MSE errors, which may suggest overly general prediction characteristics. Further analysis of FuelNet may require an architecture review or hyperparameter retuning. In summary, the LSTM2–LSTM4 models best represent the test data, while FuelNet requires further optimization.

Analysis of the fuel prediction error histograms presented in Figure 7 allows for a precise comparison of the fuel consumption prediction quality obtained by the neural models: FuelNet and LSTM 1–4. The LSTM 1 model (one LSTM layer with 64 neurons and a Dense layer), using 20 input time steps and trained for 20 epochs without dropout, generates a noticeable error peak at approximately 0.4 dm^3/h. This indicates a reproducible pattern of prediction inaccuracy and moderate model generalization. The LSTM 2 model (two LSTM layers: 64, then 32 neurons,

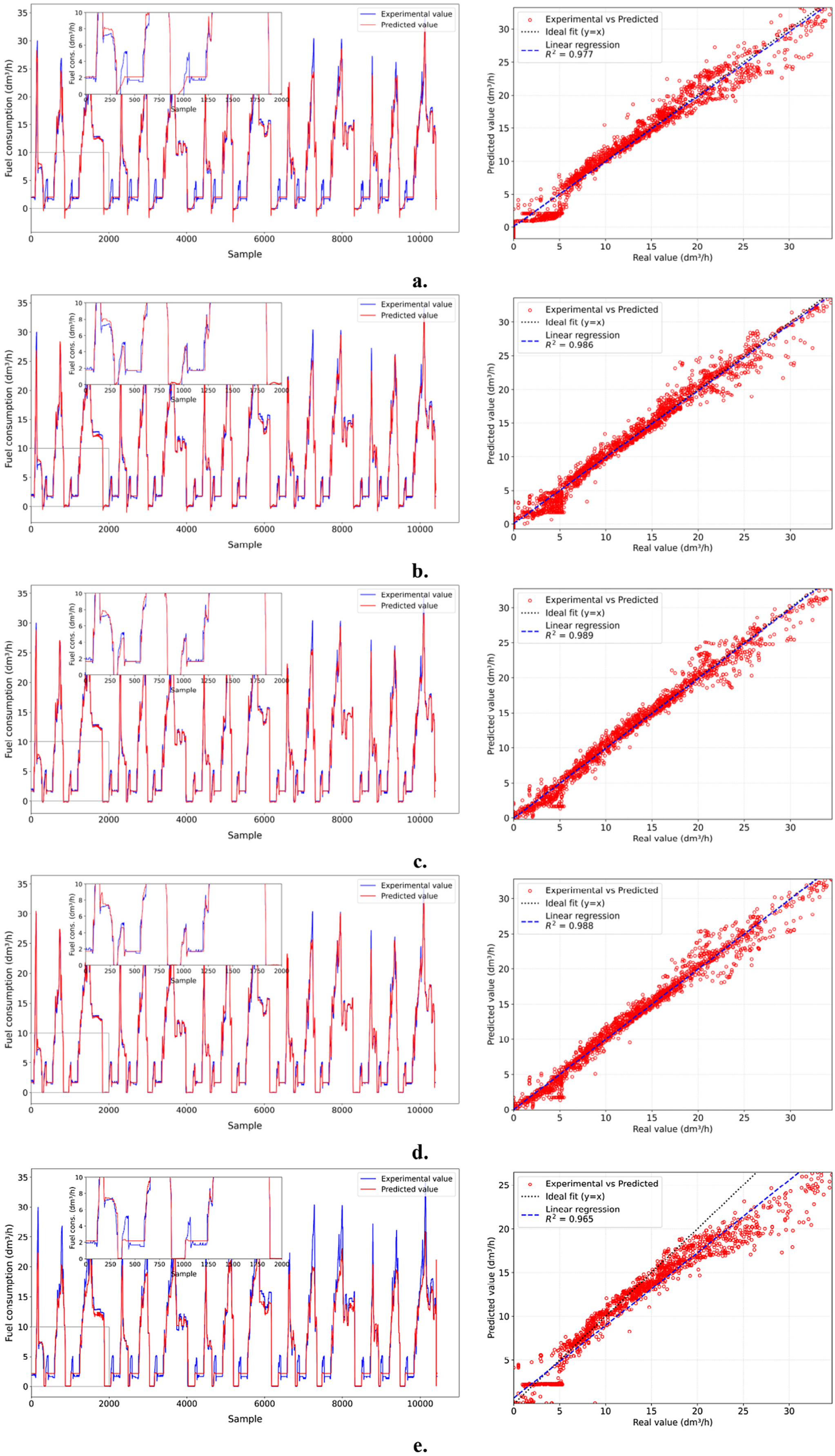

Figure 5. Results of instantaneous fuel consumption prediction for the (a) LSTM 1 model, (b) LSTM 2 model, (c) LSTM 3 model, (d) LSTM 4 model, (e) FuelNet model

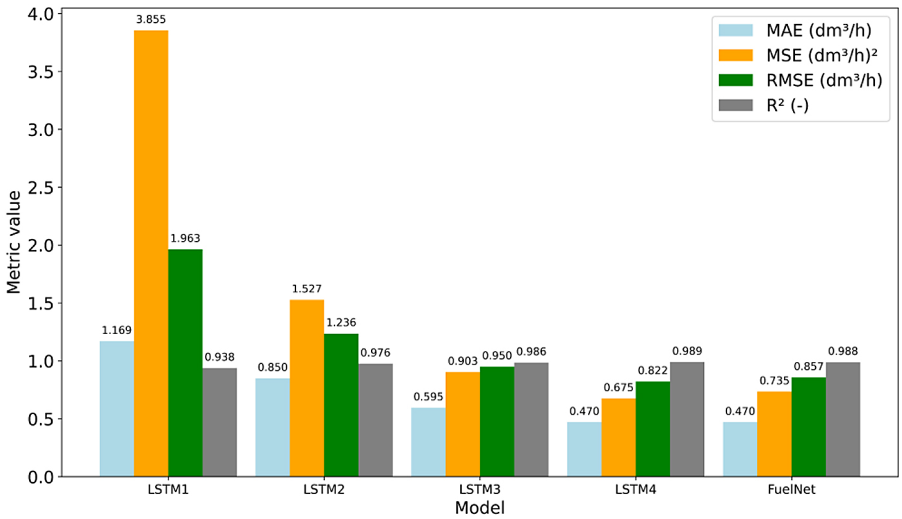

Figure 6. Model metric values

and a Dense layer) with 30 input steps, 40 training epochs, a dropout of 0.2, and MSE demonstrates a significant improvement over LSTM 1. Most errors are concentrated below 0.2 dm³/h. The introduction of dropout and a deeper structure effectively reduces overfitting. The LSTM 3 model was equipped with three LSTM layers (128, 64, and 32 neurons) and a Dense layer with 40 input steps and dynamic epoch selection (EarlyStopping), a dropout of 0.3, He normal weight initialization, and the ReduceLROnPlateau and ModelCheckpoint strategies. Error analysis revealed a significant increase in prediction accuracy. Errors in the range of up to 0.2 dm³/h are dominant.

The LSTM 4 model, which is an extension of the LSTM 3 model architecture with

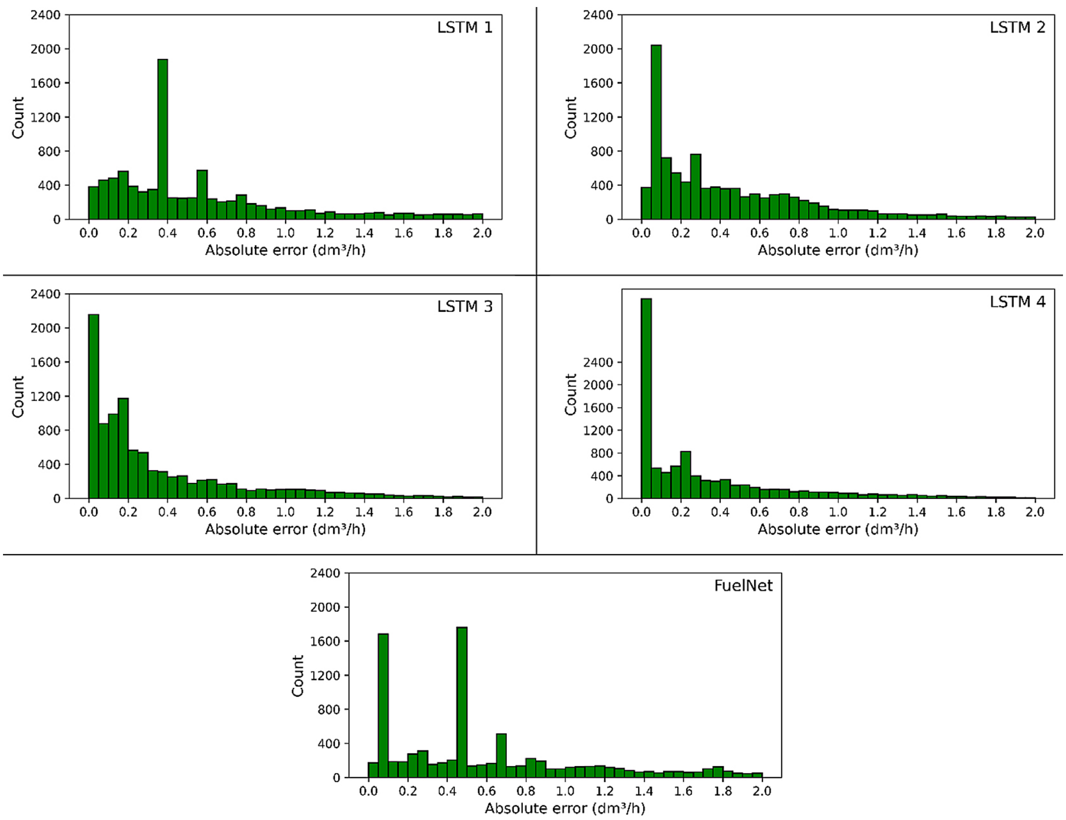

Figure 7. Fuel prediction error histograms for FuelNet and LSTM 1-4 models

identical layer parameters, input sequence, and training strategy (EarlyStopping, dropout 0.3), differs in its use of a weighted error function (weighted MSE). By taking into account lower fuel consumption values (idle mode < 2 l/h), it achieves the highest concentration of low absolute error values among the analyzed models, clearly dominating for errors below 0.2 dm³/h. The FuelNet model, based on a classic MLP (Multilayer Perceptron) network composed of 5 dense layers (Dense), without taking into account the data sequence (flat input structure), is characterized by two distinct absolute error modes around 0.05 and 0.45 dm³/h. The use of a dynamic number of epochs (EarlyStopping), an MSE loss function, and a dropout of 0.2 provides moderate precision, but a wide error distribution is visible, which may result from the simplified network structure.

To sum up, it can be stated that the use of an extensive LSTM network architecture and advanced regularization techniques (EarlyStopping, ReduceLROnPlateau, ModelCheckpoint) and a weighted error function, as in the case of LSTM 4, enabled achieving the highest precision in fuel consumption prediction. The next step in the analysis of the fuel consumption prediction modeling results was to develop box plots for the errors of each prediction. The results are shown in Figure 8. The graph compares the distributions of absolute error (dm³/h) for fuel consumption predictions for five models. Visualization in the form of boxplots enabled the analysis of basic descriptive statistics – quartile values, interquartile range, and the number and spread of outliers.

All LSTM models achieve low median errors (below 0.5 dm³/h). This demonstrates their high central precision. In the case of the FuelNet model, this median is higher, around 0.8 dm³/h. Larger differences are visible in the interquartile range (IQR). LSTM 3 and LSTM 4 models have the lowest IQR, indicating stable and predictable results. FuelNet, on the other hand, has the widest range between the lower and upper quartiles, resulting from greater error variability. The outlier analysis shows that FuelNet generates a significantly larger number of outliers, including errors exceeding 4 dm³/h. In LSTM models, this dispersion is smaller, with outliers not exceeding 6 dm³/h. However, it is worth emphasizing that the lower quartile (Q1) in all models is at a similar level – below 0.25 dm³/h – meaning that in the top 25% of cases, each model achieves high accuracy regardless of the architecture used.

In summary, LSTM models demonstrate better stability and lower error variability compared to FuelNet. Despite the potential advantages of its greater architectural complexity and flexibility, FuelNet exhibits significantly more outliers and a wider error range. This may indicate its susceptibility to overfitting or a stronger response to unusual input data. Statistical analysis suggests that model selection should consider not only average accuracy but also prediction stability and robustness to anomalies, especially in real-world applications.

The instantaneous fuel consumption prediction results obtained by the LSTM models

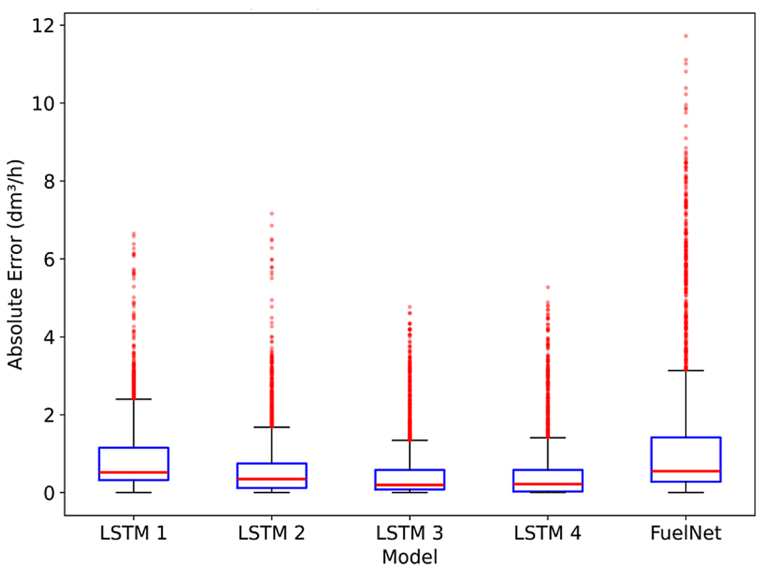

Figure 8. Comparison of absolute errors (in dm³/h) of fuel consumption prediction for different model variants

(particularly LSTM3 and LSTM4) and the FuelNet model are characterized by high quality of representation of actual values – the coefficient of determination R^2 exceeds 0.98, and the MAE oscillates in the range of 0.47–0.49 dm³/h for the best models. This accuracy classifies these models as highly useful for practical applications, such as driving style optimization or decision support systems in fleet management.

The literature on the subject reports varying levels of prediction accuracy, depending on vehicle type, environmental conditions, the number of input variables, and the modeling strategies used. To verify the quality of the obtained results, a review of current works published in high-ranking scientific journals was conducted.

In article [31] utilized a long short-term memory (LSTM) neural network to estimate instantaneous fuel consumption of a Toyota Camry HEV (hybrid electric vehicle). Authors were used GPS position, speed, acceleration, and road condition data. They achieved excellent predictive performance, with R^2 values close to 0.97–0.98 and MAE in the range ~0.3–0.4 dm³/h under real driving conditions. In comparison, LSTM3 and LSTM4 models achieved MAE < 0.5 dm³/h and $R^2 > 0.98$

In the study [32], a hybrid deep learning model (LSTM-MVO) was used to predict fuel consumption and CO_2 emissions based on OBD (on-board diagnostics) interface data, achieving high determination coefficients ($R^2 = 0.996$ for training data and $R^2 = 0.988$ for testing data). These results indicate the high effectiveness of sequential models in representing temporal and nonlinear dependencies in transport data.

In [33], the authors presented a model for estimating monthly vehicle fuel consumption and CO_2 emissions using driver behavior data (aggressive acceleration, braking, speeding) together with trip distance and duration. The best results were achieved with the Random Forest Regression model, reaching $R^2 = 0.975$, RMSE = 13.3 kg, and MAE = 8.3 kg. In the present study, the LSTM3 and LSTM4 models, developed for predicting instantaneous fuel consumption in urban traffic, achieved MAE < 0.5 dm³/h and $R^2 > 0.98$. Compared to the approach of Wang [33], which operates on monthly aggregated data, the proposed LSTM models provide high-resolution, time-series-based predictions better suited for dynamic traffic conditions.

Against the background of the above publications, it can be stated that the LSTM3 and LSTM4 models obtained in this study achieve one of the highest R^2 values (0.986–0.989) and absolute error (MAE < 0.5 dm³/h) under complex test conditions and real urban data. Furthermore, the use of sample weighting for idle mode (LSTM4) allows for better representation of significant low fuel consumption periods, which is different from the reviewed literature models.

CONCLUSIONS

The research carried out aimed to develop, implement and compare five variants of models based on neural networks for predicting instantaneous fuel consumption in city buses. Real-world data recorded during Sort 2 driving cycles were used. Analysis of the modeling results demonstrated high predictive accuracy for all models. The more advanced LSTM architectures (LSTM2, LSTM3, LSTM4) were found to be superior to the basic model (LSTM1) and the classic MLP network (FuelNet). The key findings from the study are presented below.

High prediction accuracy of LSTM models: The LSTM2, LSTM3, and LSTM4 models achieved R^2 coefficients of determination ranging from 0.986 to 0.998 and MAE values of 0.47 to 0.49 dm³/h. In particular, the LSTM4 model, with a weighted loss function that accounted for idle mode (< 2 l/h), achieved the highest precision ($R^2 = 0.99$). This highlights the importance of specialized modeling strategies for specific operating conditions, such as low fuel consumption in urban traffic.

Advantages of sequential LSTM models over classic MLP networks: The FuelNet model, based on a five-layer MLP architecture, achieved $R^2 = 0.938$, but generated larger errors (MAE and MSE) and exhibited a wider error distribution compared to LSTM models. This is due to FuelNet's limited ability to model dynamic changes in sequential data.

Effectiveness of advanced regularization and optimization techniques: The use of techniques such as EarlyStopping, ReduceLROnPlateau, and ModelCheckpoint in the LSTM3 and LSTM4 models allowed for dynamic optimization of the training process, minimizing overfitting, and achieving stable and predictable results. The introduction of a weighted loss function in the LSTM4 model further improved prediction accuracy in low fuel consumption ranges, crucial for the efficiency of bus fleets.

Prediction stability of the LSTM models: Box plot analysis showed that the LSTM models had a smaller interquartile range (IQR) and fewer outliers compared to the FuelNet model. The median error for the LSTM models was below 0.5 dm^3/h. This demonstrates their high stability and resilience to data anomalies, which is important in real-world fleet management applications.

Practical application: The high accuracy and stability of the LSTM3 and LSTM4 models demonstrates potential utility in fleet management systems or driving style optimization. The ability to precisely predict fuel consumption, especially during idling, can contribute to reducing operating costs and emissions. This is consistent with sustainable transport goals and the target decarbonization targets by 2040.

Directions for Further Research: Despite the high results obtained, further work should focus on testing the models in more diverse road and environmental conditions. This will allow us to verify the model's robustness to data variability. Furthermore, integrating a larger number of input variables, such as weather data or passenger load, could increase the models' versatility.

The study confirms that advanced LSTM models, especially those with a weighted loss function, offer high precision and stability in predicting instantaneous fuel consumption in city buses. These results could significantly contribute to the development of fuel consumption modeling methods and enable practical applications in fleet management.

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