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DEVELOPING THE MATLAB TOOLBOX FOR DETERMINING THE REAL-WORLD DRIVING CHARACTERISTICS OF VEHICLES

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Abstract. The real-world driving features of a vehicle play an important role in determining its actual fuel consumption and emissions features. The driving data on the road, instant speed versus time, is always collected to explore these characteristics. The collected data may include random errors that need to be processed before being used in further calculation steps. This study seeks to provide a useful tool for addressing data preprocessing and quantifying actual driving features. A seven-step data filter was created and incorporated into the established toolbox. The outcomes of data processing and parameters of real-world driving characteristics are presented on the graphical user interface of the built toolbox. Vehicle-specific power distribution, frequently utilized in fuel consumption and emission simulation software, is also computed using the toolbox. The proposed toolbox, therefore, can be utilized to support determining the vehicle's emission factors, which serve as an effective data source for the integrated strategies in Vietnam's air quality control.

Keywords: driving characteristics, data preprocessing, VSP, toolbox, IVE, MOVES.

1. INTRODUCTION

The transport sector always plays a vital role in the economy and society's development; it is an indispensable component of today's economy. However, this sector's strong dependence on fossil fuels, with nearly 91% of its final energy demand [1], has been causing negative impacts on human life. In 2022, global CO_2 emissions from the transport sector reached nearly 8 Gt CO_2, an increase of 3% compared to the one in 2021 [1]. In Vietnam, the share of greenhouse gas (GHG) emissions from the transport sector reached 18% of the energy sector's total GHG emissions. Among them, roads have the most significant proportion of GHG emissions, accounting for about 80% of the total GHG emissions of the entire industry [2]. Transport-related GHG emissions are projected to grow by 6.4% per year from 2014 to 2030, corresponding to about 89.1 million tonnes of CO_2 in 2030 [2]. Consequently, it is imperative to rigorously regulate pollutant emissions from the transport sector, particularly in light of Vietnam's commitment to attaining net-zero emissions by 2050.

A vehicle's emission profile is influenced by various elements, including road infrastructure, traffic density, driving patterns, engine specifications, powertrain technologies, carried load, and surrounding atmospheric conditions[3]. In the case of some factors related to technology, load, and ambient air being fixed, the real-world driving feature becomes the unique factor that affects the emissions and fuel consumption (FC) of the vehicle. The difference between driving patterns may result in significant variations in the vehicle's FC and emissions [4, 5]. Many previous studies have shown that the real-world driving characteristics of vehicles, as shown by the driving cycle, can vary from one region to another. For instance, the study of Hung et al. [6] for cars in Hong Kong, Tong et al. [7] for motorcycles (MC) and light-duty vehicles in Vietnam, Liu et al. [8] for light-duty vehicles in China, and so on. Consequently, the vehicle's driving characteristics on the road are consistently included as key input variables in the FC and emission simulation models for vehicles. This implies that collecting the vehicle's real-world driving characteristics is necessary to determine the actual FC and emission features of the vehicle.

The vehicle's realistic driving characteristics are frequently captured by collecting the instantaneous speed against time at one-second intervals using various techniques [9]. Subsequently, the data will be processed to derive driving kinematic parameters, which are representative of real-world driving behavior [10]. Among these kinematic parameters, some parameters can be used in developing typical driving cycles or as explanatory variables in the vehicle's emission and FC prediction models. For instance, Amirjamshidi and Roorda [11] used 13 driving kinematic parameters to construct the characteristic driving cycle for trucks in Canada, Nguyen et al. [12] utilized 14 parameters to develop the typical driving cycle for buses in Vietnam, Liu et al. [13] also used 14 parameters to develop the typical driving cycle for a plug-in hybrid electric bus in China, Nguyen et al. [14] created an instantaneous FC prediction model for motorcycles in Vietnam based only on a unique driving kinematic parameter. In other words, the vehicle's driving characteristic parameters are vital information for studies relating to the vehicle's FC and emissions.

In Vietnam, multiple prior studies have focused on identifying on-road driving behavior and characteristics of vehicles. For instance, Tong et al. [7] mentioned the real-world driving characteristics of MC and light-duty vehicles in developing the typical driving cycles. In addition, the driving characteristics of Hanoi's MCs and buses on the road have also been identified in some of our recent studies (see [15, 16]). However, these published results focus only on some vehicle types for some specific areas and lack the instantaneous driving characteristic parameters such as instant speed, instant acceleration, and instant vehicle-specific power (VSP). Meanwhile, many of the vehicle’s FC and emissions prediction models require input data as a series of instantaneous values or their frequency distribution. In addition, in our previous studies, real-world driving data is always taken into the data preprocessing to denoise the original data before calculating the driving characteristic parameters [15, 16]. This task is challenging for users because it necessitates coding the entire procedure.

Considering the aforementioned factors, this study seeks to develop a practical tool that assists users in analyzing real-world driving behavior or in generating relevant input parameters for vehicle FC and emission simulation models. This study further expands the application scope of the toolbox compared to the toolbox developed by Le et al. [17] to enhance its applicability across a wider range of vehicle types and driving characteristic parameters. This study also supports the input data preparation for two common emission simulation software today, IVE and MOVES. This will facilitate the determination of emission factors based on the realistic driving characteristics and extend applicability to various vehicles, rather than being limited to motorcycles using a single regression model as in [17].

2. METHODOLOGY

The general framework for developing the MATLAB toolbox aimed at identifying real-world vehicle driving characteristics is illustrated in Fig. 1.

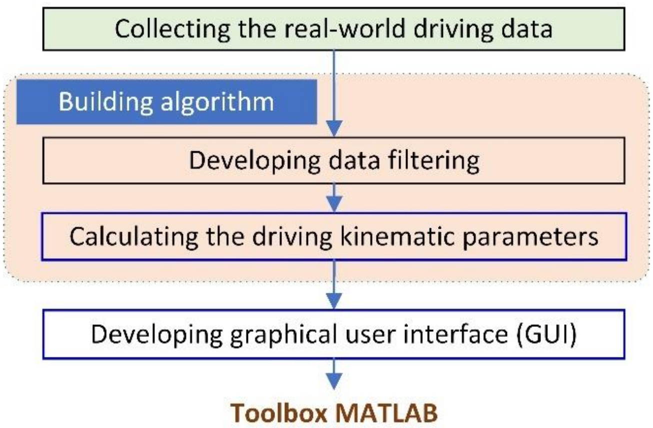

Figure 1. The procedure for developing a toolbox in MATLAB.

2.1. Collecting real-world driving data

Three primary approaches used to collect the vehicle’s driving data on the road consist of the chase car method, on-board measurement, and the application of Global Positioning System (GPS) technology [9]. Fig.3 below describes the above methods. It is noted that the vehicle driving data on the road needs to be collected continuously with a 1Hz data update rate to avoid missing information. Furthermore, it is essential to collect data continuously at one-second intervals to ensure that the driving kinetic parameters calculated based on the collected dataset align with the definitions consistently employed in studies relating to the vehicle’s driving characteristics, test cycles, and emission rates [10]. A GPS device was employed to gather real-time driving data of the test motorcycle on the road, recorded second-by-second, to obtain the sample data for further toolbox testing.

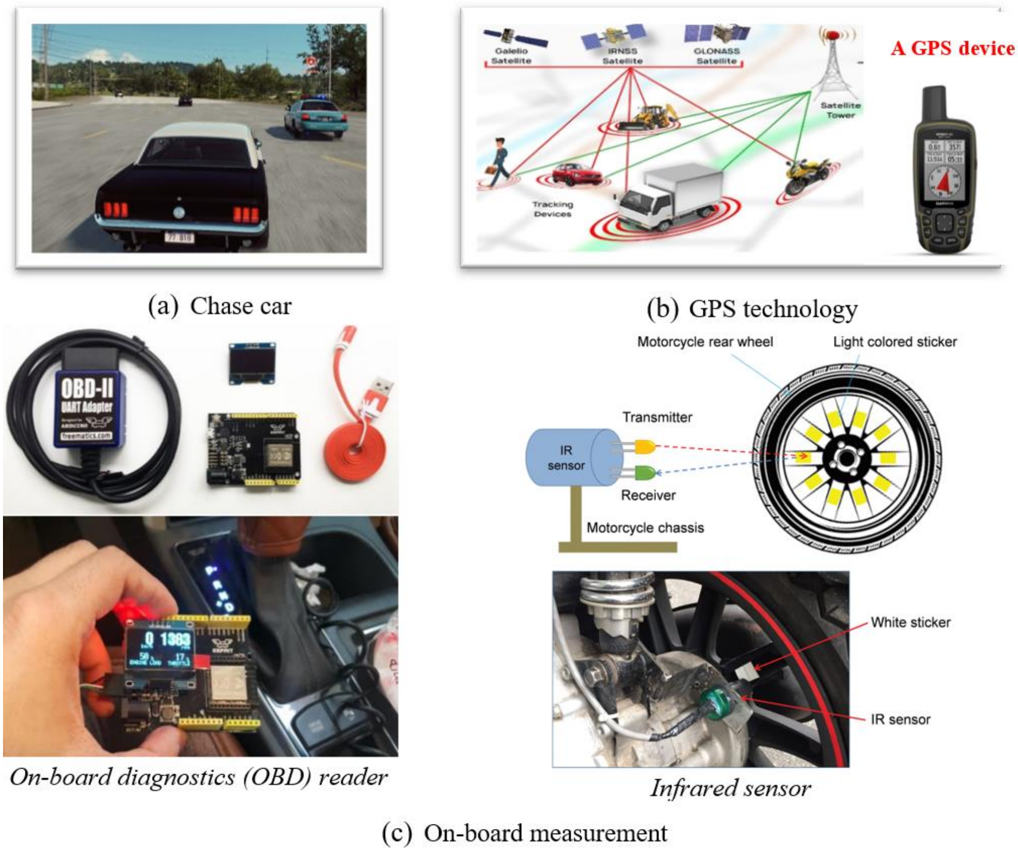

Figure 2. Examples of methods for collecting the real-world vehicle's driving data.

2.2. Developing data filtering

The acquired dataset may contain random errors such as repeated records, signal dropouts, anomalous values, and speed fluctuations[12, 18]. Consequently, it is essential to mitigate these errors prior to determining the vehicle's driving characteristic values. Therefore, this study designed a data filter of seven main steps arranged in increasing complexity order to denoise the collected data as illustrated in Fig. 3.

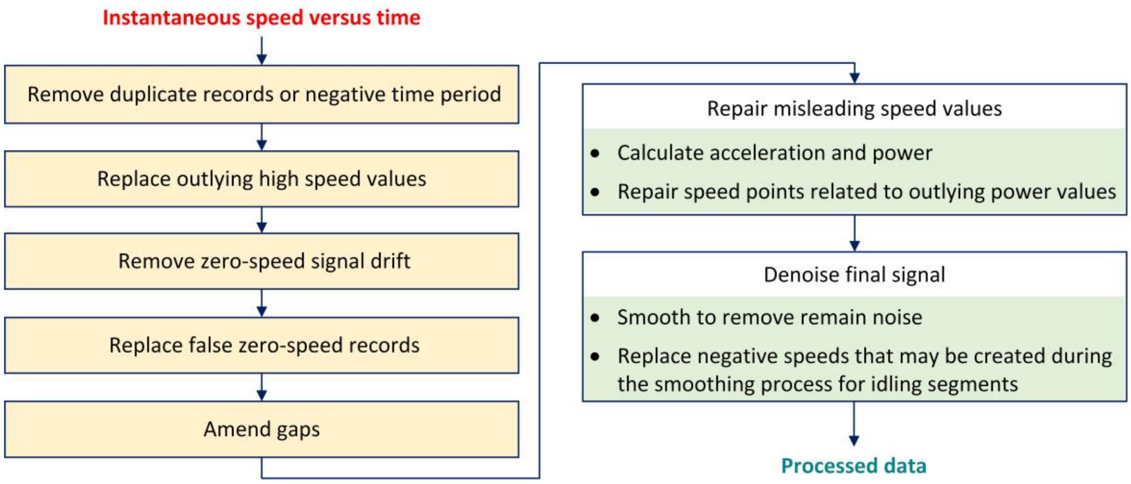

Figure 3. Flowchart of instantaneous speed series processing.

The operational principles of steps 1 to 5, emphasised in yellow, were delineated in our prior study [19]. The remaining misleading speed values that contribute to the extraordinarily high-power values will be continuously eliminated by scrutinizing the abnormal values in the instant engine power. In which the maximum power value of the engine will be used to detect these abnormal values. The instant engine power is determined according to Eq. (1) [20].

$$P = \frac{(100 + a) \times m \times VSP}{100} \tag{1}$$

Where: P denotes the engine power (kW), a denotes the power train loss (%), m is the vehicle mass (tons), and VSP denotes the vehicle-specific power (kW/ton).

The general formula of VSP is given by the United States Environmental Protection Agency (US EPA) based on the typical values as follows [21, 22]:

With: $$VSP = (1.1 \times acc + 9.81 \times gr + 0.132) \times v + 3.02 \times 10^{-4} \times v^3 \tag{2}$$

Where: v is the instant speed (m/s), acc is the instant acceleration (m/s^2), and gr is the road grade.

The filter would remove the speed value at the position corresponding to the misleading power data point to create a gap if this power value at this position exceeds the chosen limits. Subsequently, the filter will add a new speed value that is estimated using Selesnick's algorithm [23] into this gap.

Next, the Wavelet denoising method will be employed to eliminate any remaining noise in the instantaneous speed data during the final stage of the filtration process; this step is also known as the smoothing process. The fact is that the Wavelet denoising algorithm has been built as a function and a package app provided in MATLAB.

2.3. Calculating driving characteristic parameters

The preprocessed instant speed data was utilized to extract the driving kinematic parameters for vehicles under real-world driving conditions. Five groups of driving kinematic parameters will be focused on as follows:

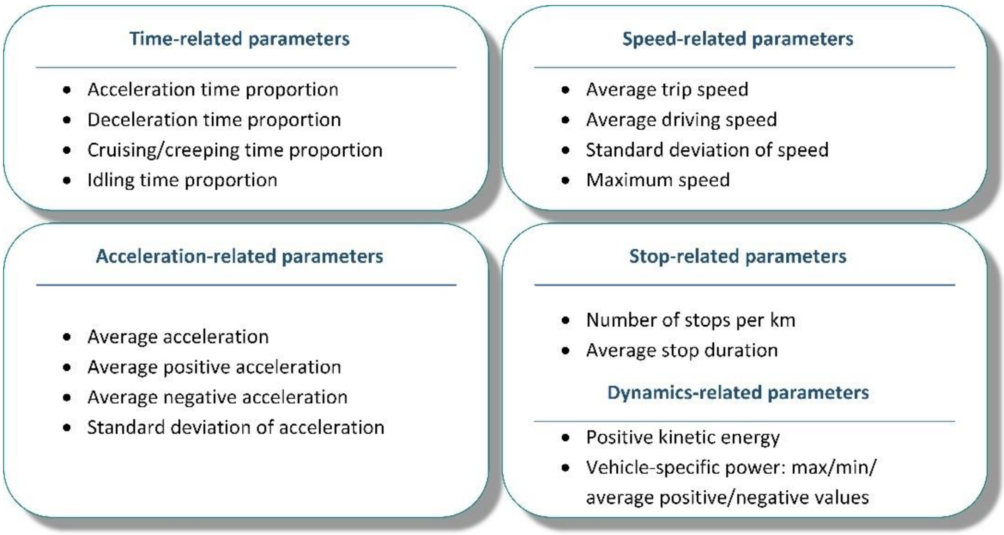

Figure 4. Groups of driving kinematic parameters.

These parameters are defined over a velocity time series comprising n data points, each with a time t_i (in seconds) and a corresponding speed v_i (in kph), as detailed in Table 1 based on the study of Barlow et al. [10].

Table 1. Definitions of kinematic parameters for driving cycles.

Parameters	**Definitions**
Distance	$Dist = (t_2 - t_1)\frac{v_1}{3.6} + \sum_{i=2}^{n}(t_i - t_{i-1})\frac{v_i}{3.6}$
Total time	$T\_total = t_2 - t_1 + \sum_{i=2}^{n}(t_i - t_{i-1})$
Cruising time	$T_c = \begin{Bmatrix} t_2 - t_1\ (\lvert a_1\rvert < 0.1\, m/s^2\ and\ v_1 > 5\, m/s \\ 0\ (else) \end{Bmatrix} + \sum_{i=2}^{n}\begin{Bmatrix} t_i - t_{i-1}\ (\lvert a_i\rvert < 0.1\, m/s^2\ and\ v_i > 5\, m/s \\ 0\ (else) \end{Bmatrix}$
Creeping time	$T_{cr} = \begin{Bmatrix} t_2 - t_1\ (\lvert a_1\rvert < 0.1\, m/s^2\ and\ v_1 < 5\, m/s \\ 0\ (else) \end{Bmatrix} + \sum_{i=2}^{n}\begin{Bmatrix} t_i - t_{i-1}\ (\lvert a_i\rvert < 0.1\, m/s^2\ and\ v_i < 5\, m/s \\ 0\ (else) \end{Bmatrix}$
Acceleration time	$T_{acc} = \begin{Bmatrix} t_2 - t_1\ (a_1 > 0.1\, m/s^2 \\ 0\ (else) \end{Bmatrix} + \sum_{i=2}^{n}\begin{Bmatrix} t_i - t_{i-1}\ (a_i > 0.1\, m/s^2 \\ 0\ (else) \end{Bmatrix}$
Deceleration time	$T_{dec} = \begin{Bmatrix} t_2 - t_1\ (a_1 < -0.1\, m/s^2 \\ 0\ (else) \end{Bmatrix} + \sum_{i=2}^{n}\begin{Bmatrix} t_i - t_{i-1}\ (a_i < -0.1\, m/s^2 \\ 0\ (else) \end{Bmatrix}$
Idling time	$T_{idle} = \begin{Bmatrix} t_2 - t_1\ (a_1 = 0\ and\ v_1 = 0 \\ 0\ (else) \end{Bmatrix} + \sum_{i=2}^{n}\begin{Bmatrix} t_i - t_{i-1}\ (a_i = 0\ and\ v_i = 0 \\ 0\ (else) \end{Bmatrix}$
Driving time	$T_{drive} = T_{total} - T_{idle}$
Cruising time proportion	$P_c = \frac{T_c}{T_{total}} \times 100\%$
Creeping time proportion	$P_{cr} = \frac{T_{cr}}{T_{total}} \times 100\%$
Acceleration time proportion	$P_a = \frac{T_{acc}}{T_{total}} \times 100\%$

Deceleration time proportion	$P_d = \frac{T_{dec}}{T_{total}} \times 100\%$
Idling time proportion	$P_i = \frac{T_{idle}}{T_{total}} \times 100\%$
Average trip speed	$V_1 = 3.6\frac{Dist}{T_{total}}$
Average driving speed	$V_2 = 3.6\frac{Dist}{T_{drive}}$
Standard deviation of speed	$V\_sd = \sqrt{\frac{1}{n-1}\sum_{i=1}^{n} v_i^2}$
Acceleration average	$a\_av = \frac{1}{N}\sum_{i=1}^{n} a_i$ (where N = T-total)
Average positive acceleration	$a\_pos\_av = \left(\sum_{i=1}^{n}\begin{Bmatrix} 1(if\, a_i > 0) \\ 0(else) \end{Bmatrix}\right)^{-1} \times \sum_{1}^{n}\begin{Bmatrix} a_i(if\, a_i > 0) \\ 0(else) \end{Bmatrix}$
Average negative acceleration	$a\_neg\_av = \left(\sum_{i=1}^{n}\begin{Bmatrix} 1(if\, a_i < 0) \\ 0(else) \end{Bmatrix}\right)^{-1} \times \sum_{1}^{n}\begin{Bmatrix} a_i(if\, a_i < 0) \\ 0(else) \end{Bmatrix}$
Standard deviation of acceleration	$Acc\_sd = \sqrt{\frac{1}{n-1}\sum_{i=1}^{n} a_i^2}$
Number of stops	$N\_stop = \sum_{i=1}^{n}\begin{cases} 1(\{v_i = 0 \wedge a_i = 0\} \wedge \{v_i \neq 0 \vee a_i \neq 0\}) \\ 0(else) \end{cases}$
Stops per each kilometer	$N\_rate = 1000\frac{N\_stop}{Dist}$
Positive kinetic energy	$PKE = \frac{1}{dist} \times \sum_{i=2}^{n}\begin{Bmatrix} v_i^2 - v_{i-1}^2(if\, v_i > v_{i-1}) \\ 0(else) \end{Bmatrix}$
Root mean square of acceleration	RMSA = $\sqrt{\frac{1}{T}\int_0^T a^2 dt} = \sqrt{\frac{1}{N}.\sum_{i=1}^{N} a_i^2}$ where: N = T = T_total

This study will also provide calculations for the distribution of VSP into bin groups as defined in the IVE and MOVES software. This software is frequently utilized in research concerning the vehicle's FC and emissions in Vietnam. The VSP bin distribution is used as a unique input variable associated with the vehicle's actual driving characteristics. Therefore, the developed toolbox MATLAB will support preparing the vehicle's actual driving feature-related input variable for the software to become more convenient.

2.4. Developing a graphic user interface

In this study, a graphic user interface (GUI) was developed in MATLAB. Five core functions are developed for this GUI consisting of importing data, modifying data, cleaning data, calculating driving characteristic parameters, and displaying the result.

Importing data: The vehicle's instant speed values versus time were imported directly from Excel files that consist of two columns of time and speed.

Modifying data: In the collected dataset, the time was recorded in the format of HH:MM:SS. Consequently, to facilitate processing data and calculating the vehicle’s driving characteristic parameter, this data must be converted from the time moment to a second. After that, The initial time value was normalized to zero, and subsequent time points were recalculated as the offset relative to this reference.

Cleaning data: The data modified above would be brought in the filter of seven main steps with the algorithm as mentioned above.

Calculating driving characteristic parameters: Twenty driving characteristic parameters will be calculated based on the processed data. In addition, the distribution of VSP into bin groups that were defined in the IVE and MOVES software would also be calculated.

Displaying the result: the vehicle’s driving characteristic parameters were displayed in the developed GUI. In addition, this study also developed a feature that enables the direct export of Bins-related results for MOVES and IVE into an Excel file located in the toolbox's code-containing folder.

3. RESULTS AND DISCUSSION

3.1. Evaluation of the filter effectiveness

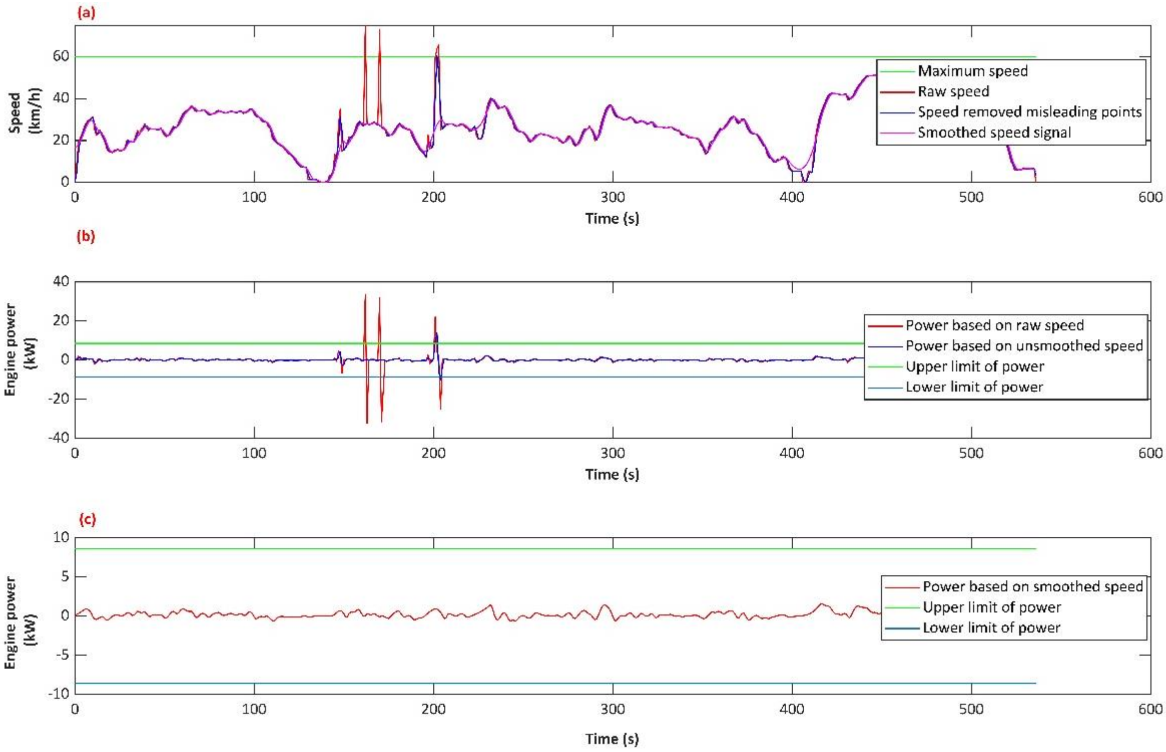

Figure 5. Illustration of the effectiveness of the designed filter.

Initially, the filter's effectiveness was validated based on the logical structure of its processing procedure. As previously stated, all outlier high-speed values were identified, and removed to generate gaps; then, Selesnick's missing data estimate algorithm was employed to fill these gaps. The reliability of the proposed approach was validated in our previous research (see [12]). The fact is that random errors in the instant speed profiles may still appear even when the outlier high-speed points are removed due to the energy mismatch of two adjacent speed values. For example, at time t = 202s and t = 203s, engine power values that were calculated based on the instant speed values exceeded the limit of engine power (Fig.5b) even when the outlier speed values at these positions were removed (Fig.5a). However, these outlier engine power values no longer exist in the final signal as can be seen in Fig. 5c. Because the denoising process was performed in the last step of the filter for the speed dataset, which had previously eliminated misleading values as presented in Fig.5c (legend of denoised speed). This implies that the logic of the designed filter is suitable and close. The obtained result is also consistent with the judgment given by Duran and Earleywine [18].

Secondly, the designed filter's effectiveness was demonstrated through the smooth technique chosen and used in the last filtration step. This study performed a comparison of the denoising effectiveness of other methods, including the Kalman filter, Savitzky-Golay filter, and Wavelet denoising algorithm. Among them, the Savitzky-Golay filter was used successfully in [18]; the Kalman filter was applied in many recent studies, as shown in [12, 24, 25]; and the Wavelet denoising algorithm was used in [26, 27]. These three techniques are developed as functions available in the MATLAB software library. The standard test cycle of the World Motorcycle Test Cycle (WMTC) was used as a dataset without noise, known as the original signal, to test denoising techniques. A noise signal was added to the original signal in this study as presented in Fig.6. After that, three denoising techniques mentioned above were utilized to denoise. The effectiveness of these techniques was analyzed and given in Fig.7 and Table 1.

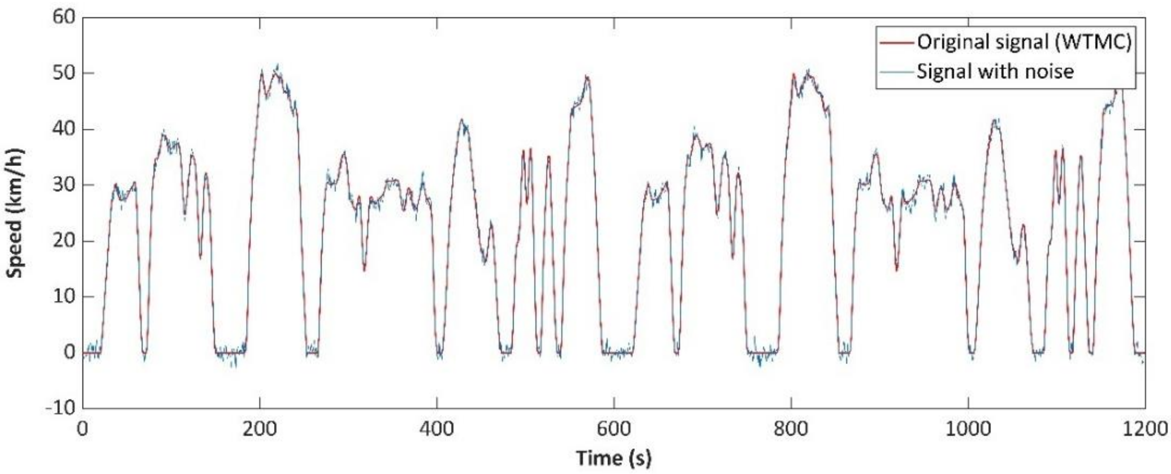

Figure 6. Original signal (WTMC) and signal with noise.

As can be seen in Fig.6, for idling mode-related segments, the signal with noise may show negative speed values due to the randomness of the noise generation process. As a result, the denoised signal could also contain negative speed values, as demonstrated in Fig.7. This study, therefore, assessed the efficacy of denoising algorithms in two scenarios: retaining the negative noise values before denoising and substituting the negative noise values with the actual values of the original signal before denoising (Table 1).

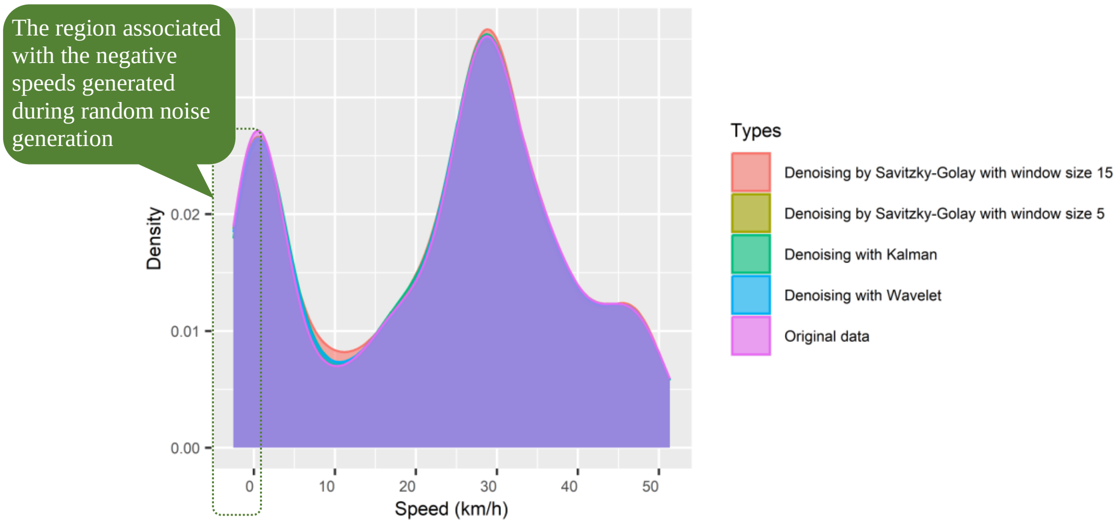

Figure 7. Comparison of speed distribution between the original data and the one denoised by various approaches.

Table 1. Estimating the effectiveness of denoising techniques.

Cases	**Considered aspects**	**Comparison with the original data**			
		Savitzky-Golay (window size 5)	Savitzky-Golay (window size 15)	Wavelet	Kalman
Including negative noise values	Overlap rate in the instant speed distribution (%)	99.5	98.1	99.4	99.0
	Average absolute error (km/h)	0.5	0.8	0.5	1.0
Not including negative noise values	Overlap rate in the instant speed distribution (%)	98.9	97.6	98.7	98.3
	Average absolute error (km/h)	0.5	0.8	0.6	9.9
	Negative speed values proportion in the denoised signal (%)$^{(*)}$	3.1	5.3	4.2	0

Note: $^{(*)}$ percentage of total speed data points of 1200 data.

Among the smooth techniques analyzed above, the Kalman filter's efficiency is the lowest following all aspects considered, except for the proportion of zero speed values generated after the denoising process. The inaccuracy of the covariance values of the measurement and process noise could explain it. The fact is that determining the covariance values of the measurement noise and the process noise is complex, as demonstrated in [24]. This study used the covariance values of the measurement noise and the process noise for the instantaneous speed data that is collected using the GPS technology based on the study result of Jun et al. [24]. The review study indicates that, to date, no research has presented the covariance values of measurement and process noises for the vehicle's speed data obtained using alternative methods. For the Savitzky-Golay filter, Table 1 also shows that the performance of the Savitzky-Golay filter is highly sensitive to both the selected window length and the polynomial order. In fact, it is difficult to decide the window size and order for polynomial regression. Consequently, achieving high efficiency with the Savitzky-Golay filter is indeed challenging. For the Wavelet denoising technique, Table 1 illustrates that the Wavelet denoising technique achieves a denoising efficiency that surpasses that of the Kalman filter and the Savitzky-Golay filter with a window of size 15 and is comparable to the Savitzky-Golay filter with a window of size 5. The fact is that the denoising efficiency of the Wavelet method was also demonstrated in other studies. For instance, the most recent, Sahoo et al. [28] reconfirmed that the Wavelet denoising technique is an extensively used technique for enhancing the signal-to-noise ratio without distorting the signal. Various fields, including time series analysis, have implemented Wavelet denoising and recognized its superior performance in comparison to filtering-based denoising methods [28]. In conclusion, denoising using the Wavelet method is a suitable choice for removing the remaining noise in the instantaneous speed dataset to tackle both the efficiency and convenience-related demand.

Finally, the filter has been supplemented with the ability to replace any negative speed values that may appear during the denoising process using the Wavelet-based smooth technique, even when the negative speed value proportion is very small and only exists in the idling mode-related segment. The efficiency of further processing is demonstrated in Fig. 8.

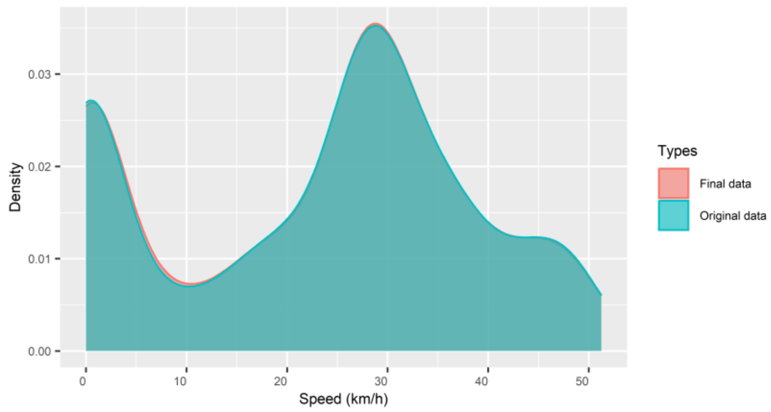

Figure 8. Comparison of the speed distribution between the original data and the denoised data by Wavelet with further processing at the last step.

As shown in Fig.8, the speed distribution of the two datasets is very similar, with an overlap of 99.7%. In addition, the negative speed values are no longer in the processed dataset.

In other words, all obtained results demonstrated the designed filter's effectiveness in terms of the logic of processing steps as well as the algorithm used. Therefore, this designed filter procedure will be brought into the GUI development process.

3.2. GUI for determining the real-world driving characteristics of vehicles

In this work, a MATLAB toolbox was created to remove noise in the real-world driving data and calculate the driving characteristic parameters. Fig.9 shows the stages of the toolbox in detail. These steps are arranged in three main sectors: importing data, processing data, and viewing results.

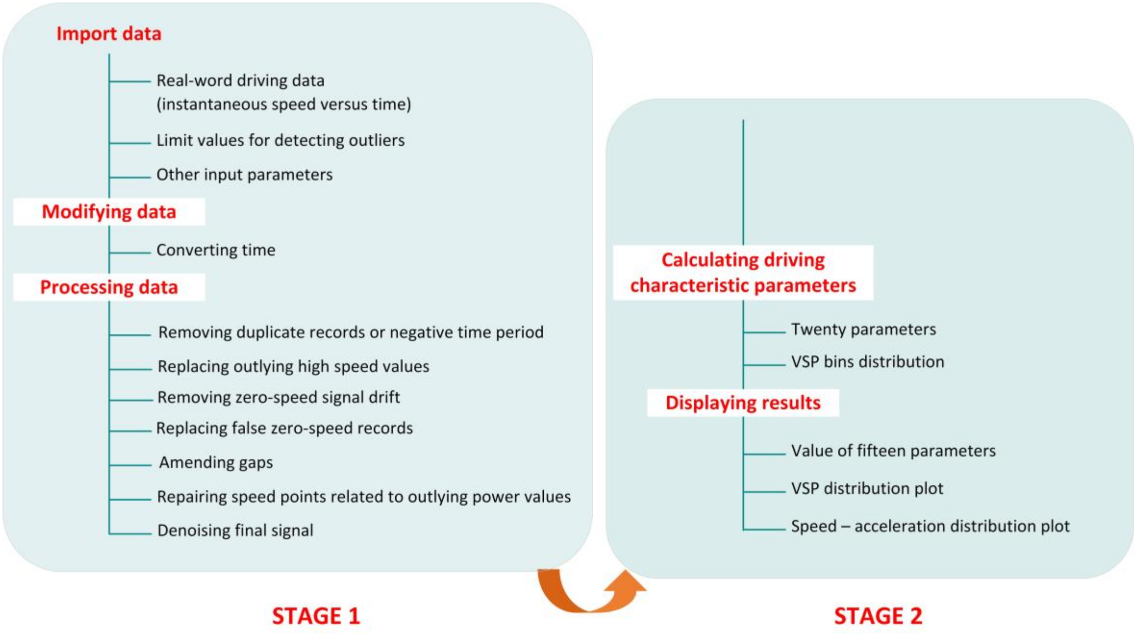

Figure 9. Process of the toolbox.

The developed toolbox offers user-friendly functionality, requiring only the import of input data via the GUI (see Fig.10); then, it can carry out data pre-processing as well as calculate the vehicle’s actual driving characteristic parameters automatically. The processed data along with the computed driving parameters are automatically stored in the directory where the MATLAB toolbox is stored. In addition, as can be seen in Fig.10, this study used the “pop-up menu” box from MATLAB’s guide to create a choice of vehicle types during the calculation process, consisting of electric vehicles (EV) and internal combustion engine-used vehicles (ICE). This is to create convenience for users while ensuring the accuracy of the data processing step based on the engine power compatibility check. Because the power train loss value (a) is necessary to calculate P (see Eq.1) but it is difficult for users to know.

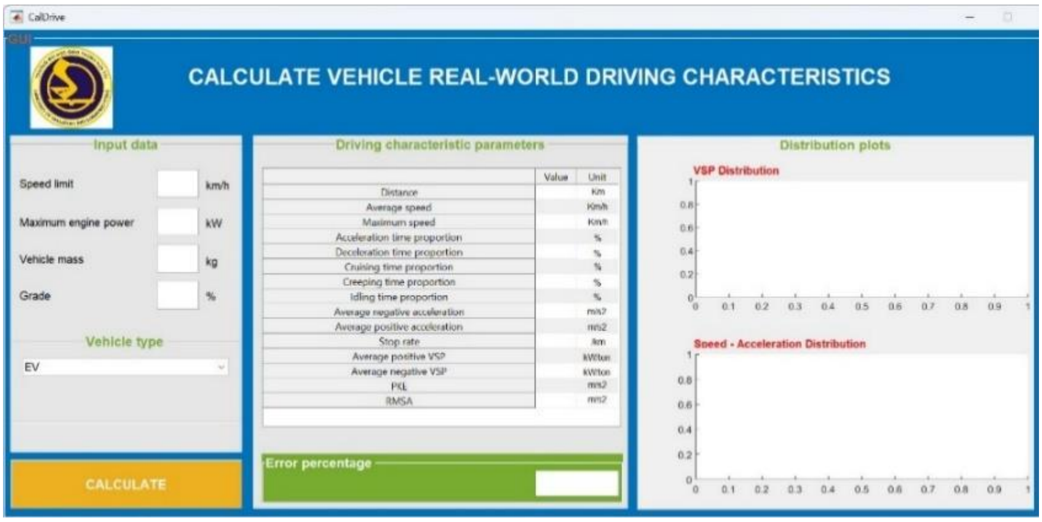

Figure 10. Interface of the toolbox.

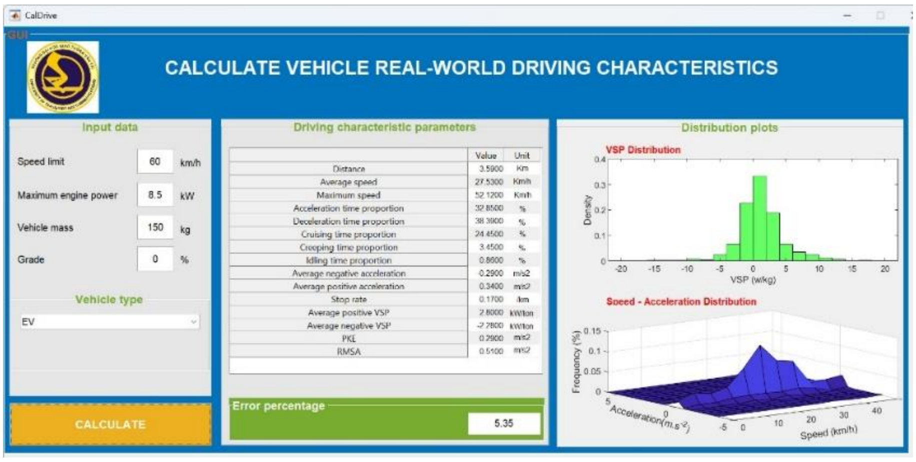

Figure 11. Display results.

In this study, the VSP bins distribution according to the definition used in the IVE software [29] and MOVES software [30] is also calculated, exported to an Excel file, and stored in the pathway mentioned above. In addition, this study also designed the GUI to show fifteen driving characteristic parameters that are commonly used in the vehicle’s emissions and FC prediction models using average aggregate parameters such as EMFAC and COPERT [31] as presented in Fig.11. These provide convenience for users who want to study vehicle emissions using emission simulation methods.

4. CONCLUSIONS

The vehicle’s real-world driving characteristic was focused on in this study due to their importance in vehicle emissions and FC-related studies. This feature is often captured by the instantaneous speed values versus time, second-by-second; after that, the real-world driving kinematic parameters will be calculated based on the gained instant speed series. However, the gained instant-speed data always contains noise, including random errors, that can impact the accuracy of driving kinematic parameters. Therefore, a seven-step data filter was developed and verified using the original data of WTMC. This study demonstrated that checking the agreement of two adjacent speed values is required even if the outlier high-speed values have been eliminated to ensure proper engine power. In addition, future research investigations are also recommended to recheck the smoothed speed signal to replace the negative speed values that may appear during the smoothing process for the idling-related data segments. This study also reconfirms the surpassed denoising efficiency of the Wavelet denoising technique compared to the Kalman filter and the Savitzky-Golay filter.

A GUI toolbox was built on MATLAB to simultaneously perform both data processing and calculation of vehicle real-world driving characteristics. The GUI is designed to be very simple and convenient for the user. The developed GUI will be a valuable tool for studies related to the simulation of vehicle emissions and FC.

For user simplicity, this study excluded engine power associated with air conditioning operation. Consequently, the enhanced data processing step based on engine power may be affected if the actual power consumption approaches the engine's maximum power. Therefore, the developed toolbox is best applied to all motorcycles or to any automobiles where the necessary power for moving does not exceed 90% of the maximum engine power.

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