Article citation info:
Snarska-Bień G, Lasocki J. Enhancing driving cycle development using artificial intelligence. Combustion Engines. 0000;XXX(X):xx-xx. https://doi.org/10.19206/CE-209909

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Enhancing driving cycle development using artificial intelligence

ARTICLE INFO

Received: 15 June 2025
Revised: 25 July 2025
Accepted: 25 August 2025
Available online: 14 September 2025

In recent years, artificial intelligence (AI) has found application in numerous technical areas, including the automotive research and development sector. This paper considers the use of AI tools for the development of driving cycles for testing vehicles on a chassis dynamometer. The above idea was investigated on the example of a driving cycle simulating the use of a passenger car in urban conditions. The empirical data were collected during vehicle road tests in real traffic and then processed statistically by determining the values of selected driving pattern characteristics. Sections of vehicle velocity courses ('micro-trips') were selected and combined into a driving cycle representative of the road conditions prevailing during road tests. Processing of empirical data and combining velocity sections into a driving cycle was performed using AI-enhanced software utilizing large language models that convert user commands in natural language into Python code. The developed driving cycle was compared with selected standard urban driving cycles in terms of the values of driving pattern characteristics.

Key words: *driving cycle, artificial intelligence, AI, urban traffic, passenger car*

1. Introduction

The most significant negative impacts of combustion engines on the environment include exhaust emissions, which contain substances that are toxic to living organisms and contribute to climate change [13]. Additionally, the combustion of fossil fuels leads to the depletion of non-renewable natural resources [16]. Growing awareness of these threats has sparked actions against environmental degradation. They were first undertaken in the field of combustion engine applications in motor vehicles, both light- and heavy-duty, primarily due to their widespread use. Over the past few decades, significant progress has been made in this area, thanks in part to the development and validation of effective methods for testing pollutant emissions [22].

To ensure consistent testing conditions for vehicles, standardized test procedures are necessary. In the case of light vehicles, such as passenger cars and delivery vans (which are categorized according to relevant regulations), these tests are conducted under conditions that simulate traction operation. For metrological reasons, testing is carried out in laboratories using chassis dynamometers [1, 9, 24]. A crucial element of the dynamometer testing methodology, which connects the testing conditions with real driving performance, is the driving cycle [9, 11].

A 'Driving cycle' refers to a predefined sequence of vehicle velocity as a dependence of time, designed to replicate real-world driving patterns for testing purposes, typically related to emissions or fuel efficiency [3, 9, 11, 20]. Driving cycles can be divided into two categories [11]:

1. Standard cycles, which are recognized by international homologation regulations (e.g. WLTC, FTP-75, UDDS (FTP-72), HWFET, SFTP US06, SFTP SC03, NEDC, JC08, 10-15 Mode and CLTC)
2. Special cycles, which are created for specific scientific, research, and development purposes (e.g. CADC (Artemis), Autobahn, ADAC Highway Cycle, PIMOT CT, UT, RT, HT).

To date, several hundred driving cycles have been developed globally [3, 11]. The vast number of cycles can be attributed to the diverse traffic conditions they simulate, such as urban, rural, motorway, and expressway driving, as well as traffic congestion. Additionally, the development of cycles that are representative of specific geographical areas, such as countries, regions, or even cities, has contributed to the increasing number of driving cycles. This growth is further driven by advancements in the scientific foundations and methodologies used to create these cycles.

The representativeness of driving cycles relative to the actual traffic conditions they aim to simulate is influenced by four main factors [5]:

1. Quality and quantity of empirical data obtained from the vehicle road test
2. Methodology used to develop the driving cycle
3. Selection of driving pattern parameters that serve as criteria for the driving cycle's compliance with actual empirical data
4. Duration of the driving cycle.

As for the stage of collecting empirical data, currently most researchers utilize information from the vehicle's On-Board Diagnostics (OBD) system [19], and devices based on Global Positioning System (GPS) technology [28]. These tools allow for conducting low-cost, large-scale road tests, with multiple vehicles and/or drivers, providing an extensive dataset for further analysis. Additionally, the scope of these road tests can be expanded to include pollutant emission measurement using Portable Emission Measurement Systems (PEMS) [25] and visual recordings of driver behavior or the vehicle's surroundings.

Regarding the second factor, methods for developing driving cycles can be categorized into two main groups: deterministic and stochastic [8, 27], with further subdivisions according to minor methodological nuances.

The most commonly utilized deterministic approach is the trip-based method, where each vehicle trip recorded during data collection can be selected as a representative driving cycle using criteria based on the similarity of driving pattern parameters, such as average velocity or average acceleration. This method is repeatable, generating the same driving cycle each time for the same input data and similarity criteria.

The primary stochastic methods include the Markov chain-Monte Carlo method and the micro trip method [30]. In the first one, the velocity course of the driving cycle is generated artificially through a detailed analysis of road test data. Velocity and acceleration matrices are created along with the probabilities of specific states defined by velocity and acceleration. The order of these states is then selected using a pseudo-random Monte Carlo method [15, 30]. In the micro trip method, all recorded velocity courses from road tests are divided into micro trips by isolating from each velocity course individual sections that cover the vehicle's movement: starting from a complete stop, traveling at a non-zero velocity, braking to a stop, and the subsequent period of time when the vehicle remains stationary. Then, the sections are selected and connected in a quasi-random manner until the assumed total cycle time is reached [8]. Additionally, microtrips can be grouped into clusters based on common features, typically utilizing two or three selected parameters [31]. The main advantage of these stochastic methods is that the generated driving cycle is not identical to any samples recorded during empirical tests. Consequently, a different driving cycle can be obtained each time, even with the same input data.

Since pollutant emissions and fuel consumption of vehicle engines are exclusively tied to the conditions under which the vehicle is tested, meaning a specific driving cycle with a defined velocity course, it becomes essential to establish criteria for assessing these velocity courses. In principle, the basis for quantitative assessment should be numerical estimates [33]. For a specific time course of velocity, these numerical estimates are referred to as 'driving pattern parameters' or ‘zero-dimensional characteristics’ [2, 7, 20]. The quality of these parameters is determined by their effectiveness for a particular application.

While some driving pattern parameters, such as average and maximum velocity, average positive and negative acceleration, and the share of driving and standing time, are widely recognized, there is no consensus on the best set of parameters to describe vehicle velocity patterns effectively. Numerous examples of driving pattern parameters can be found in the extensive literature on the topic [3, 4, 27]. To ensure that the developed driving cycle accurately represents the simulated road conditions, driving pattern parameters must be determined and compared for the driving cycle’s velocity course and the entire set of velocity samples from road tests [7, 27]. The above criterion is considered to be fulfilled if the values of the driving pattern parameters in both scenarios are similar and if the fuel/energy consumption and pollutant emissions of a given vehicle during normal use align with those observed in the driving cycle on a chassis dynamometer.

The duration of the driving cycle is also an important factor [12]. Long cycles can be costly to conduct and may exceed the capabilities of laboratory equipment, such as the capacity of exhaust gas bags, while shorter cycles may increase the measurement uncertainty. In practice, the duration of the driving cycle depends on the developer, as there is no consistent, recognized methodology in this field. Many of the common driving cycles are typically around 20 minutes long [27].

In recent years, artificial intelligence (AI) has found application in numerous technical fields, including automotive research and development. AI is a general term that encompasses several specific domains, such as machine learning, fuzzy logic, computer vision, evolutionary computing, and neural networks. The scientific literature highlights the application of certain AI features in the context of developing driving cycles. For example, Jia et al. [17] proposed a new method for generating driving cycles for heavy-duty vehicles using the Markov Chain method together with an average velocity-based matching algorithm. Mostasharshahidi et al. [23] examined the impact of learning-based AI algorithms on constructing driving cycles for off-road vehicles, namely agricultural tractors. Sankar et al. [29] employed a constrained genetic algorithm to optimize the vehicle velocity when creating a driving cycle oriented towards fuel consumption and driver comfort. Qiu et al. [26] demonstrated a data-driven, recurrent neural network-based method to develop driving cycles for light-duty vehicles in Beijing that simulate actual driving patterns. Gebisa et al. [10] utilized a neural network and principal component analysis to create a driving cycle for passenger cars using real-time data from Addis Abeba. Londoño et al. [21] proposed a methodology to identify the most representative motorcycle driving patterns across various topographies, taking into account factors like elevation above sea level and slope variations, using AI techniques such as support vector machines and clustering.

The purpose of this paper is to demonstrate the feasibility of using AI tools based on natural language processing to develop driving cycles. A case study of a driving cycle designed to simulate urban traffic conditions for a passenger car is presented. The cycle was generated based on empirical data collected from road tests of a vehicle in real traffic. The velocity course constituting the driving cycle was generated using the micro-trip method, where individual velocity sections were selected and compiled by AI. Finally, the developed driving cycle was compared with selected standard urban driving cycles in terms of the values of driving pattern characteristics.

2. Materials and methods

2.1. Research framework

The subsequent section outlines the research framework of this study. Section 2.2 provides an overview of the collection of road traffic data, including the technical specifications of the vehicle and the test equipment used. Section 2.3 introduces the main methodological assumptions regarding the procedures adopted for processing empirical data to construct the driving cycle, the selection of driving pattern characteristics as criteria for the representativeness of the developed driving cycle, and the duration of the cycle. Finally, section 2.4 describes the AI-based software that supports the development of the driving cycle.

2.2. Experimental data collection

Road tests were conducted to gather statistical data on vehicle driving under the urban conditions considered, which later served as the foundation for developing a representative driving cycle. The tests were conducted in Warsaw. To account for the random nature of the vehicle driving conditions, no specific route or time of day was designated. The same driver operated the vehicle throughout the tests. The methodology involved having the driver follow another randomly selected road user, thereby replicating their driving style.

The object of the road tests was a city passenger car – a hatchback from segment B, equipped with a spark-ignition combustion engine. Figure 1 shows the test vehicle, while its technical specifications are presented in Table 1.

Fig. 1. Vehicle used for the road tests

Table 1. Technical specifications of the tested vehicle

Parameter	Unit	Value
Engine type		Spark-ignition
Fuel		Gasoline
Engine displacement volume	cm^3	1596
Arrangement and number of cylinders		Inline, 4
Fuel supply system		Indirect, multi-point injection
Engine maximum power /at rotational speed	kW/rpm	88/6000
Engine maximum torque /at rotational speed	Nm/rpm	152/4050
Axle driven		Front
Vehicle curb mass	kg	1045
Transmission type		Manual, 5-speed
Production year		2011
Emission class		Euro 5

During road tests, the following driving parameters were recorded:
- vehicle velocity [km/h]
- engine rotational speed [rpm]
- accelerator pedal relative position [%]
- coolant temperature [°C]
- engine relative load [%]
- air mass flow rate [g/s]
- air temperature in the intake manifold [°C]
- air pressure in the intake manifold [kPa]
- fuel pressure in the supply system [kPa]
- voltage at the battery terminals [V].

These driving parameters were recorded directly from the vehicle's OBD system using the TEXA OBD Log (Fig. 2). The technical specifications of the device can be found in Table 2.

Fig. 2. TEXA OBD Log used to collect data in road tests

Table 2. Technical specifications of TEXA OBD Log

Parameter	Unit	Value
Processor		ARM 32-bit Contex-M3
RAM	kB	256
Internal memory	kB	2048
Maximum data recording time	h	90
Maximum sampling frequency	Hz	1
Operating temperature range	°C	–40 to +85
Software		IDC3 PC Suite
PC interface		USB 1.0 cable
Power supply in the vehicle		OBD 12 V connector

A total of 250 samples, which contain data from individual 'journeys', that is, periods of vehicle use from engine startup to shut down, were collected through road tests. The samples underwent preliminary screening, and those with a travel time exceeding 180 s and an average velocity of no less than 10 km/h were arbitrarily accepted for further analysis [19]. Such a selection criterion aimed to eliminate the few samples recorded during heavy traffic jams, treating such conditions as a distinct category of road traffic [6]. Ultimately, 242 vehicle velocity course samples that met the above-mentioned requirements were utilized as the basis for developing the driving cycle.

The statistical parameters of the vehicle velocity courses for 242 qualified measurements were as follows:
- total duration of all journeys – 214,067 s (almost 60 h)
- average duration of a single journey – 885 s (almost 15 min)
- average driving velocity – 24.82 km/h
- average maximum velocity – 74.61 km/h
- average time share of stops – 28.84%
- average number of stops – 15
- average duration of a single stop – 16 s
- average number of changes in the sign of the velocity derivative (in 100 s) – 2
- average number of accelerations and decelerations in a single journey – 153.

2.3. Main methodological assumptions

In this study, the driving cycle was developed using the micro-trip method. Each recorded trip was divided into sections that begin and end with the vehicle stopped, i.e. when the vehicle's velocity is zero and the engine is idling. The idling time at the end of the micro trip was included. These sections were then randomly combined using the AI tool. The goal was for the values of the selected driving pattern parameters to closely match those of the entire data set from the empirical studies (section 2.2).

The driving pattern parameters adopted as criteria for evaluating the driving cycle included:
– average vehicle velocity
– maximum vehicle velocity
– time share of vehicle stops (with the engine idling).
The number of criteria parameters was intentionally kept limited to avoid complicating the optimization task assigned to the AI software. Thus, no parameters related to acceleration and deceleration were introduced, assuming compliance of their values, as they were derived from actual fragments of velocity courses from the road tests.

The duration of the driving cycle was arbitrarily set at 1200 s, which is similar to the timeframes of typical urban cycles, such as JC08, NEDC, or FTP-72 [3, 11]. The WLTC, currently in force in the European Union and some other countries, lasts 1800 s, but accounts for urban, rural, and highway driving conditions. In addition, it was assumed that the driving cycle would begin and end with a short phase (5 s) of the vehicle being stopped with the engine idling.

The work on the driving cycle proceeded gradually. Initially, an attempt was made to create a driving cycle for 15 velocity samples. Once this procedure was mastered, the same process was repeated for all 242 samples from the empirical studies. Input commands were formulated for the AI software, and the resulting outputs were analyzed. This process provided the authors with valuable experience in working with the program, and the resulting observations and recommendations are included in the discussion section of this paper.

The following order of commands was ultimately established for the AI software:
1. Load a CSV file containing empirical data
2. Calculate driving pattern parameter values for the empirical data (target values)
3. Split the empirical data (velocity courses) into micro-trips
4. Compile micro-trips into a driving cycle, aiming to obtain driving pattern parameter values as closely aligned with the target as possible
5. Analyze the developed driving cycle
6. Iteratively improve the cycle until the new version achieves driving pattern parameter values closer to the target.

Exemplary prompts entered into the program are included in section 3.5 of the paper.

In this study, the authors adopted a guiding principle that allowed the AI to find its own method for generating a synthetic driving cycle. Therefore, a specific data processing algorithm was not imposed, and a degree of randomness in the selection of micro-trips was intentionally allowed, with the only restrictions being those mentioned above.

2.4. AI software

The processing of empirical data and the compilation of velocity sections into a driving cycle were performed using the AI software Julius. This software is designed for analytical statistics, data science, and computations. It operates on the principle of leveraging large language models (LLMs), such as OpenAI's ChatGPT and Google Gemini, which convert user commands entered in natural language into Python code. For more information about Julius, please refer to [18].

The program features a straightforward interface that facilitates a dialogue with the user. Commands were entered sequentially in a logical order (as outlined in section 2.3), rather than as a single command that would generate a driving cycle instantly.

3. Results and discussion

3.1. The developed driving cycle

Figure 3 illustrates the final version of the driving cycle that simulates urban traffic conditions, developed using the Julius AI software based on a complete set of 242 velocity samples recorded during empirical tests.

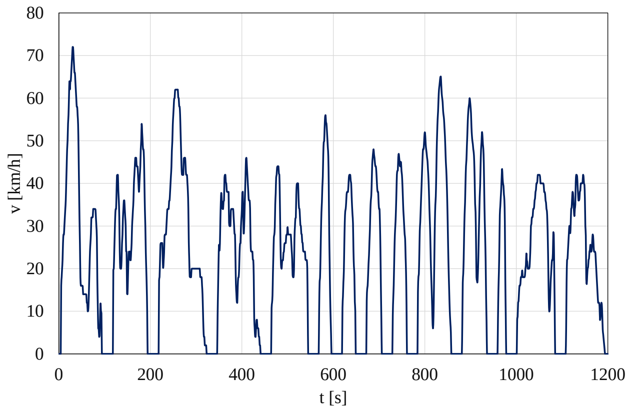

Fig. 3. Vehicle velocity course in the developed driving cycle (AI Cycle)

As can be seen in the graph, the vehicle velocity course reflects typical urban driving patterns. In urban areas, vehicle velocity fluctuates, incorporating phases of acceleration, deceleration, and idling, which capture the stop-and-go nature of city driving. This variability is attributed to various factors, including intersections controlled by traffic lights, traffic calming measures, high traffic volume, reduced velocity limits etc. Traffic lights not only cause vehicles to stop, but also slow them down as drivers anticipate stopping. Similar effects arise from traffic calming measures such as speed bumps, raised intersections, and others, leading to deceleration before and acceleration following these obstacles. Furthermore, rapid changes in vehicle speed are often influenced by the presence of numerous other road users. Finally, the peak velocities observed in the developed driving cycle are typical for urban conditions. In Polish cities, the velocity limit is 50 km/h in built-up areas, though this limit may vary based on road signs. Certain road sections within cities also allow higher velocities, such as 70 km/h.

The above-mentioned characteristic features of the developed velocity course distinguish it from the relatively smoother velocity patterns typical in rural areas and especially on highways (motorways/express roads) [6], which exhibit fewer sharp peaks and less frequent stops – often none at all.

3.2. Comparison of the developed AI driving cycle with experimental data

The selected driving pattern parameters were chosen to serve as the criteria of representativeness of the created AI driving cycle for the modeled traffic conditions. The values of these parameters were calculated and compared between the developed driving cycle and the complete set of velocity samples from the experimental data. The results are presented in Table 3.

Table 3. Comparison of driving pattern parameters determined for the developed driving cycle and all samples collected during road tests

Parameter	Unit	AI driving cycle	All velocity samples	Relative difference
Time/average time	s	1200	885	35.59%
Average velocity	km/h	22.85	24.82	–7.94%
Maximum velocity	km/h	72.00	74.61	–3.50%
Time share of stop	%	27.08	28.84	–6.10%

The driving pattern parameters determined for the developed driving cycle and the experimental data showed no significant differences. The average vehicle velocity in the driving cycle was 1.97 km/h lower than in road tests, translating to a relative change of –7.94%. The share of idling time was 1.76% lower (–6.10%), and the maximum velocity was 2.61 km/h lower (–3.50%). In terms of the duration of the developed cycle compared to the average time of a single trip during road tests, the difference is not significant, as the cycle time was chosen arbitrarily.

3.3. Comparison of the developed AI driving cycle with selected standard driving cycles

Table 4 presents a comparison of selected parameters of the driving cycle obtained using AI with those of selected standard driving cycles: the Japanese JC08, American UDDS (FTP-72), European NEDC, and the global WLTC. Additionally, Figure 4 graphically compares the velocity courses of the developed driving cycle with those of the aforementioned standard cycles.

Table 4. Comparison of selected parameters of the developed driving cycle and selected standard driving cycles [11]

Parameter	Unit	AI driving cycle	JC08	UDDS (FTP-72)	NEDC	WLTC Class 3-2
Time/average time	s	1200	1204	1372	1180	1800
Distance traveled	m	7616	8171	11997	11017	23250
Average velocity	km/h	22.85	24.40	31.60	33.60	46.50
Maximum velocity	km/h	72.00	81.60	91.25	120.00	131.30
Time share of stop	%	27.08	28.7	17.8	23.7	12.6

The comparison indicates that the AI-generated driving cycle is the closest to the Japanese JC08. Both cycles exhibit a similar overall character of the velocity course (Fig. 4a), nearly the same duration (1200 s vs. 1204 s), and a comparable idling time (27.08% vs. 28.70%). However, the AI cycle has a slightly lower average velocity (22.85 km/h

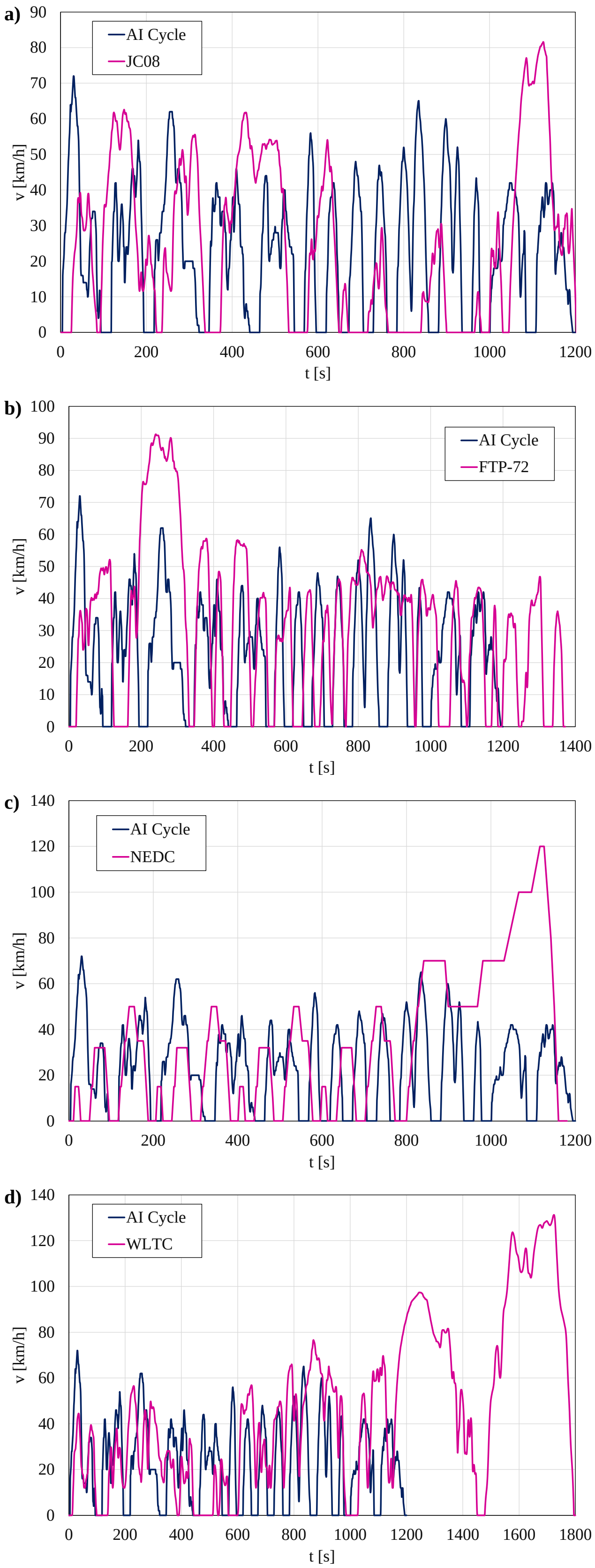

Fig. 4. Comparison of vehicle velocity courses in the developed driving cycle (AI Cycle) with those of selected standard driving cycles: a) JC08, b) FTP-72, c) NEDC, d) WLTC

vs. 24.40 km/h) and a lower maximum velocity (72.00 km/h vs. 81.60 km/h). Consequently, the lower average velocity and cycle time result in a theoretically shorter distance traveled (7616 m vs. 8171 m).

The sharp velocity peaks observed in the AI-generated driving cycle closely resemble those of the UDDS (Figure 4b). However, the American cycle includes a section where the vehicle reaches a velocity exceeding 90 km/h. When comparing the parameters of the driving patterns, the AI-generated cycle falls short of the UDDS in several areas: duration (1200 s vs. 1372 s), distance driven (7616 m vs. 11997 m), average velocity (22.85 km/h vs. 31.60 km/h), and maximum velocity (72.00 km/h vs. 91.25 km/h). Notably, the AI-generated cycle has a higher share of time spent at a stop (27.08% vs. 17.80%).

The AI driving cycle and the NEDC have a similar duration (1200 s vs. 1180 s) and a relatively close share of idling (27.08% vs. 23.70%). However, the other parameters are lower in the AI cycle compared to the NEDC: average velocity (22.85 km/h vs. 33.60 km/h), maximum velocity (72.00 km/h vs. 120 km/h), and distance driven (7616 m vs. 11017 m). This is primarily due to the NEDC's purpose of simulating both urban and extra-urban driving conditions. Additionally, the velocity courses differ, as the NEDC is a synthetic cycle composed of straight lines that correspond to the vehicle traveling at a constant velocity or with constant acceleration and deceleration.

The comparison between the AI-generated cycle and the WLTC is relevant, considering the widespread use of the latter in vehicle homologation. The AI-generated cycle exhibits significantly lower velocities, with average (22.85 km/h vs. 46.50 km/h) and maximum (72.00 km/h vs. 131.30 km/h). Similarly, the total time and distance traveled are shorter (1200 s vs. 1800 s and 7616 m vs. 23,250 m). On the other hand, the time share of the vehicle stop is higher in the AI-generated cycle than in the WLTC cycle (27.08% vs. 12.6%). It should be emphasized, however, that the WLTC simulates various driving conditions, not only urban, but also extra-urban and highway scenarios.

The similarities between the AI-generated driving cycle and standard cycles, particularly those that represent typical urban conditions (such as JC08 and UDDS), indicate that the AI-generated cycle effectively simulates real-world driving scenarios. Furthermore, these similarities reduce the risk that the developed driving cycle would be incompatible with testing equipment used for standard cycles.

From a broader perspective, the observed similarities and differences between the AI-generated cycle and the considered standard cycles could have significant practical implications. The similarities support the validity of existing standard cycles, despite evolving traffic conditions and advancements in automotive technology. However, even though standard cycles are benchmarks for policy frameworks and vehicle development, they may fall short in being responsive to some driving habits. AI applications can, in this regard, help in the development of driving cycles appropriate for given areas, conditions, or types of vehicles, thereby improving the relevance of the testing outcomes. Driving cycles based on local empirical data can capture the dynamics of vehicle performance, emissions, and fuel consumption during actual driving conditions much better than the existing standardized cycles. The adaptation of AI methodologies to generate custom cycles for various driving environments, such as rural, mountainous or congested traffic, is a promising future direction. Insights gained from these cycles, which accurately reflect actual traffic conditions, can complement the general data obtained from standardized driving cycles.

3.4. Study limitations

The resulting driving cycle can be considered a sufficient representation of the modeled vehicle motion conditions. It should be noted that this study aimed to investigate the practical aspects of using AI in developing drive cycles, rather than creating an ideal drive cycle for certain applications, such as emissions testing. Having said that, the authors of this paper identified several areas for improvement.

Firstly, the data collection stage could be expanded in quantitative terms, which would positively impact the quality of the resulting drive cycle. Further, the conditions for collecting empirical data could be specified more precisely: for instance, by designating a single route, selecting specific times of the day, involving various drivers and vehicles, etc. Moreover, the equipment used in the road tests was basic, allowing only the recording of fundamental parameters from the OBD system at a fairly low frequency (1 Hz). With current technical advancement, it is possible to carry out tests that include emission measurements using PEMS, although probably large-scale studies of this type would not be economically justified.

Secondly, at the stage of generating the driving cycle, it would have been beneficial to further refine the velocity profile to obtain driving pattern values even closer to those characterizing all samples from the road tests. In this respect, the authors decided that the obtained results were acceptable and decided not to pursue further enhancements. Additionally, more driving pattern parameters could be included, along with those related to acceleration.

Thirdly, the developed driving cycle should be verified on a chassis dynamometer in terms of its feasibility and subsequently validated on the basis of pollutant emission and fuel consumption results in road tests, i.e. RDE, as well as in standard cycles.

3.5. Precision of commands given to AI

While working on the driving cycle, the authors gained experience in cooperation with AI software. The key issue that determined the efficiency of the process and the quality of the results was the precision of the formulated commands. All user intentions had to be articulated clearly and precisely, e.g. *"Create a new combined speed profile using different speed sections with adjacent idle time sections in between. Take into account the following target parameters: total duration 1200 s, average speed 24.82 km/h, maximum speed 74.61 km/h, percentage idle time 28.84%"*.

In the initial iterations of developing the driving cycle, some inconsistencies appeared. For example, one version of the cycle began and ended with a vehicle velocity different from zero, which is rarely used from the point of view of practical implementation of the cycle on a chassis dynamometer (e.g. the non-standard Autobahn cycle). For this reason, the program received an additional line of command to ensure the cycle started and ended with a few seconds of engine idling with zero velocity: *"Add 5 seconds idling at the beginning and at the end of the cycle"*.

As with natural language processing used for creating images or videos, a single prompt may provide a completely different driving cycle, even when based on the same set of empirical data. Therefore, it is difficult to discuss the repeatability of the results in a strict sense. However, the proposed procedure allows for reproducibility of the results, understood as obtaining a set of similar driving cycles with driving pattern parameters close to the target values.

3.6. Uncertainty of AI-derived results

An important aspect of working with AI is the concern about the uncertainty of the results obtained using uncontrolled 'hidden' internal algorithms of such tools. This phenomenon is called the 'AI black box problem' [14], which refers to the lack of transparency or the limited transparency in how machine learning systems process the inputs through complex algorithms and generate outputs. As a result, it may be difficult or impossible to understand how the AI tool reached its conclusions. This issue is becoming increasingly important, not only in technology but also in fields such as healthcare, safety, and security [32].

However, the AI black box problem is of lesser concern in this study for two reasons. Firstly, the AI tool used translates natural language commands into explicit Python code, which is fully visible and can be independently inspected and verified by the user. This allows for rigorous checking of the code correctness before execution, mitigating concerns related to hidden algorithmic processes. Additionally, the primary criteria for the driving cycle validity are its empirical representativeness and practical applicability in dynamometer testing, rather than the internal workings of the AI. To safeguard accuracy, the AI-generated driving cycle was compared with real traffic data and standard driving cycles. This confirmed that – theoretically – the cycle reliably reflects urban driving conditions. The final proof of the cycle adequacy will be the empirical testing of pollutant emissions and fuel consumption, which is planned (see section 3.7). Thus, the combination of code transparency and empirical verification addresses the 'black box' concerns in this study context.

3.7. Future perspectives

The approach outlined in this paper, along with the case study example, does not comprehensively cover this broad subject. There are many directions for further research in this field, the prospects of which have opened up with the rapid development of AI in recent years.

First and foremost, the presented AI-enhanced approach for driving cycle development requires empirical validation. The authors plan to utilize the developed cycle to conduct tests on pollutant emissions and fuel consumption on a chassis dynamometer. This will involve comparing the results with those obtained using standard urban driving cycles. Such testing would provide evidence for the practical applicability and accuracy of the AI-enhanced development approach – a critical validation step to confirm the cycle's suitability for regulatory and research purposes.

The authors believe that the optimal way for AI to assist in creating driving cycles would be to produce entirely artificial velocity courses that fully meet the criteria and requirements set by researchers. According to the experimental data from road tests, the primary goal would be to ensure that every driving pattern parameter selected has the same value for the developed cycle and the set of experimental data. Furthermore, the ability to generate these kinds of driving cycles within a short timeframe would make it possible to introduce the idea of testing a vehicle's fuel consumption and pollutant emissions on a chassis dynamometer under random or pseudo-random conditions. This is in line with the stochastic approach to evaluating vehicle performance.

4. Summary and conclusions

This study explored the potential application of AI tools to generate driving cycles, which are essential for assessing pollutant emissions and fuel consumption in passenger vehicles on a chassis dynamometer. This theoretical concept was illustrated through a case study focused on an urban driving cycle. The AI tool employed was based on software that utilizes natural language processing to convert user commands into programming code. The resulting driving cycle was generated according to similarity criteria of several driving pattern characteristics, namely: average vehicle velocity, maximum vehicle velocity, and the time share of vehicle stop with the engine idling.

In summary, the following conclusions and observations can be drawn from this study:

– The developed driving cycle demonstrated the feasibility of using AI tools in developing driving cycles
– AI-driven natural language processing tools are efficient and convenient for driving cycle development, though they do have certain constraints and challenges for beginners
– Data processing using AI tools significantly speeds up the development of driving cycles
– Precise command formulation is essential when using AI tools, as vague instructions may result in inaccurate outcomes
– The proposed method allows for the creation of a wide variety of driving cycles for light vehicles, motorcycles, and heavy vehicles, while accommodating different traffic scenarios, including urban, extra-urban, and motorway conditions
– Further development work on the proposed general approach is needed, mainly for the empirical verification of pollutant emissions and fuel consumption based on these driving cycles.

While the full potential and operational rules of AI have yet to be thoroughly explored, it is reasonable to assume that driving cycle development will benefit greatly from its application in the future. It can significantly enhance the processing of large volumes of road test data, allowing for the generation of driving cycles that accurately reflect specific road conditions. Additionally, it supports the idea of conducting chassis dynamometer tests with randomly selected driving cycles following a stochastic approach.

Nomenclature

ADAC	Allgemeiner Deutscher Automobil-Club
AI	artificial intelligence
CADC	Common Artemis Driving Cycles
CLTC	China Light-duty Vehicle Test Cycle
FTP	Federal Test Procedure
GPS	global positioning system
HWFET	Highway Fuel Economy Test
JC	Japan Cycle
LLM	large language model
NEDC	New European Driving Cycle
OBD	on-board diagnostics
PEMS	portable emission measurement systems
RDE	real driving emissions
SFTP	Supplemental Federal Test Procedure
UDDS	Urban Dynamometer Driving Schedule
WLTC	Worldwide Harmonized Light Vehicle Test Cycle

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