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CONDITIONS FOR OPTIMIZING POWERTRAIN PERFORMANCE IN A VEHICLE WITH AN INTERNAL COMBUSTION ENGINE

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Abstract

The paper presents optimization of the drive system in terms of adapting it to the characteristics of another engine. Powertrain parameters in a vehicle with an internal combustion engine were selected based on the following criteria: fuel consumption, engine dynamics, and emission standards for harmful substances. A light-duty passenger vehicle with gross vehicle weight rating (GVWR) of 3.5 tons was modified by replacing a spark-ignition engine with a diesel engine. The gear ratio in the powertrain had to be modified accordingly to optimize the engine's performance, enhance engine dynamics, minimize fuel consumption and toxic emissions. The optimization of selected parameters of the vehicle driveline was performed based on the requirements of the standard NEDC and WLTC cycles.

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Introduction

The design of new vehicles and the upgrading and adaptation of the existing vehicles require optimization techniques for reducing the time and cost of these operations. Optimization techniques also facilitate the search for trade-off solutions that account for different and often contradictory customer requirements.

The process of upgrading vehicles with internal combustion engines involves the reduction of engine capacity, improvement of the power-to-weight ratio, the introduction of turbochargers, cylinder deactivation systems and start-stop systems to minimize fuel consumption in urban traffic. FRASER et al. (2009) analyzed the extent to which a decrease in engine cylinder capacity reduces fuel consumption. The study was conducted on a D-segment car where a 2.0 L TGDI engine was replaced with a 1.2 L MAHLE engine. Driving cycle tests revealed a 15% decrease in fuel consumption.

The main goals of modern vehicle design, upgrade and operation are to reduce power consumption, increase energy efficiency and minimize vehicles' negative impact on the environment. These processes rely on optimization techniques that considerably reduce the time and cost of investments in the automotive industry. Optimization techniques are deployed to improve structural solutions in vehicles (FRIES et al. 2018, LI et al. 2020, OGLIEVE et al. 2017, WENCHEN et al. 2016) and to adapt vehicles to operational environments (BERTRAM, HERZOG 2013, SKUGOR, DEUR 2014, PENG at al. 2018).

To further the development of effective automotive solutions and modern powertrain systems, optimization techniques were used in this study to improve selected operating parameters of a vehicle with an internal combustion engine. Quality criteria, functional limitations and decision parameters need to be established to fully harness the potential of optimization techniques. Such analyses should also consider the operating conditions of vehicles and systems whose performance is determined by many interacting processes. The results of such studies can be used to identify the available scope for potential improvement in powertrain systems.

Analysis of a vehicle's operating parameters as optimization criteria

Criteria for evaluating a vehicle's energy consumption

A vehicle's energy consumption is measured in kWh. The volume of energy consumed per unit distance is determined in kWh/km, and the same measure can be applied to evaluate powertrain performance. In a vehicle with an internal combustion engine, energy consumption is normally expressed in terms of fuel

consumption per unit of distance, usually L/100 km (kg/100 km). The demand for energy in a vehicle with an internal combustion engine can be expressed with the use of the below formula (KROPIWNICKI 2011):

$$E = \int_0^{t_c} (F_{rf} \cdot V) \,\mathrm{d}t \tag{1}$$

where:

 t_c – cycle time,

 F_{rf} – total resistive forces acting on a moving vehicle, V – vehicle's linear velocity.

The following resistive forces act on a vehicle:

- rolling friction $F_{f'}$
- air resistance F_{air}
- gradient resistance F_q ,
- inertial resistance F_i ,
- internal resistance F_{int} .

Rolling friction can be described with the following formula:

$$F_f = f_r \cdot m \cdot g \cdot \cos \alpha = f \cdot Q_i \tag{2}$$

where:

 f_r – coefficient of rolling friction,

m – vehicle mass.

- α road gradient,
- Q_i tire-ground interaction force.

Air resistance is calculated as follows (MITCHKE 1977):

$$F_{\rm air} = \frac{c_x \cdot \rho_a \cdot A \cdot v^2}{2} \tag{3}$$

where:

 C_x – coefficient of aerodynamic resistance,

 ρ_a – air density,

 $A - \operatorname{car}$ frontal area,

v – linear velocity.

Gradient resistance is determined based on the following formula:

$$F_g = m \cdot g \cdot \sin \alpha \tag{4}$$

Inertial resistance is associated with translational motion or rotational motion of an object (GILLESPIE 1992, MITCHKE 1977, ORZEŁOWSKI 1969). It is generally calculated with the use of the following equation:

$$F_i = m \cdot \delta \cdot \frac{\mathrm{d}v}{\mathrm{d}t} \tag{5}$$

where:

 $\frac{\mathrm{d}v}{\mathrm{d}t}$ – linear acceleration,

dt 5 - coefficient for converting the inertia of rotating components to the inertia of translational motion.

The sum of resistive forces:

$$F_{rf} = F_f + F_{air} + F_g + F_i \tag{6}$$

is used to determine instantaneous power demand:

$$P_r = F_{rf} \cdot V \tag{7}$$

The thrust force produced by the engine shaft and a vehicle's velocity can be expressed as follows (GILLESPIE 1992):

$$F_t = \frac{M \cdot i_g \cdot i_o \cdot \eta_t}{r_d} \tag{8}$$

$$V = \frac{\pi \cdot n \cdot r_d}{30 \cdot i_g \cdot i_o} \tag{9}$$

where:

M - torque,

n – rotational speed of the engine shaft,

- i_a gear ratio of the gear box,
- i_o gear ratio of the final drive,
- r_d dynamic rolling radius.

A vehicle's maximum velocity in a given driving environment can be determined with the use of the dynamic coefficient D which is calculated as follows:

$$D = \frac{F_t - F_{\rm air}}{m \cdot g} \tag{10}$$

When the remaining resistive forces are considered, the equation can be expressed as follows:

$$D = f_r + w + \frac{\delta}{g} \cdot \frac{\mathrm{d}\nu}{\mathrm{d}t} \tag{11}$$

where *w* is the coefficient of gradient resistance: $w = \tan \alpha \approx \sin \alpha$. If the vehicle is moving on a flat roadway ($\alpha = 0$) at a constant speed ($\frac{dv}{dt} = 0$), then $D = f_r$, therefore:

$$\frac{F_t - F_{\rm air}}{m \cdot g} = f_r \tag{12}$$

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$$\frac{M \cdot i_g \cdot i_o \cdot \eta_t}{r_d} - \frac{c_x \cdot \rho_a \cdot A \cdot v^2}{2} = f_r \cdot m \cdot g,$$

$$v_{\max} = \sqrt{\frac{1}{C_x \cdot \rho_a \cdot A} \cdot \left(\frac{2M \cdot i_{g\min} \cdot i_o \cdot \eta_t}{r_d} - 2f_r \cdot m \cdot g\right)}$$
(13)

where:

 i_{gmin} – the gear ratio of the final gear.

The maximum slope that the vehicle can climb is calculated with the following formula:

$$w = D - f_r - \frac{\delta}{g} \cdot \frac{\mathrm{d}v}{\mathrm{d}t} \tag{14}$$

If the vehicle moves at a constant speed, then, therefore:

$$w = \frac{F_t - F_{\text{air}}}{m \cdot g} - f_r \tag{15}$$

The gear required to achieve the speed of V_f should be considered when calculating the acceleration of a vehicle with an internal combustion engine. If the last gear is required, and the vehicle has a five-speed gearbox, then the time needed to reach speed V_f can be calculated as follows:

$$t_{a} = \int_{0}^{V_{1}} \frac{m \cdot \delta}{\frac{P_{t}}{V_{1}} - m \cdot g \cdot f_{r} - 0.5 \cdot \rho_{a} \cdot C_{x} \cdot A \cdot V^{2}} dV + \int_{V_{1}}^{V_{2}} \frac{m \cdot \delta}{\frac{P_{t}}{V_{2}} - m \cdot g \cdot f_{r} - 0.5 \cdot \rho_{a} \cdot C_{x} \cdot A \cdot V^{2}} dV + \int_{V_{2}}^{V_{3}} \frac{m \cdot \delta}{\frac{P_{t}}{V_{3}} - m \cdot g \cdot f_{r} - 0.5 \cdot \rho_{a} \cdot C_{x} \cdot A \cdot V^{2}} dV + \int_{V_{4}}^{V_{4}} \frac{m \cdot \delta}{\frac{P_{t}}{V_{4}} - m \cdot g \cdot f_{r} - 0.5 \cdot \rho_{a} \cdot C_{x} \cdot A \cdot V^{2}} dV + \int_{V_{4}}^{V_{f}} \frac{m \cdot \delta}{\frac{P_{t}}{V_{4}} - m \cdot g \cdot f_{r} - 0.5 \cdot \rho_{a} \cdot C_{x} \cdot A \cdot V^{2}}} dV + \int_{V_{4}}^{V_{f}} \frac{m \cdot \delta}{\frac{P_{t}}{V_{4}} - m \cdot g \cdot f_{r} - 0.5 \cdot \rho_{a} \cdot C_{x} \cdot A \cdot V^{2}}} dV + \int_{V_{4}}^{V_{5}} \frac{m \cdot \delta}{\frac{P_{t}}{V_{4}} - m \cdot g \cdot f_{r} - 0.5 \cdot \rho_{a} \cdot C_{x} \cdot A \cdot V^{2}}} dV + \int_{V_{4}}^{V_{5}} \frac{m \cdot \delta}{\frac{P_{t}}{V_{4}} - m \cdot g \cdot f_{r} - 0.5 \cdot \rho_{a} \cdot C_{x} \cdot A \cdot V^{2}}} dV + \int_{V_{4}}^{V_{5}} \frac{m \cdot \delta}{\frac{P_{t}}{V_{4}} - m \cdot g \cdot f_{r} - 0.5 \cdot \rho_{a} \cdot C_{x} \cdot A \cdot V^{2}}} dV + \int_{V_{4}}^{V_{5}} \frac{m \cdot \delta}{\frac{P_{t}}{V_{4}} - m \cdot g \cdot f_{r} - 0.5 \cdot \rho_{a} \cdot C_{x} \cdot A \cdot V^{2}}} dV + \int_{V_{4}}^{V_{5}} \frac{m \cdot \delta}{\frac{P_{t}}{V_{4}} - m \cdot g \cdot f_{r} - 0.5 \cdot \rho_{a} \cdot C_{x} \cdot A \cdot V^{2}}} dV + \int_{V_{4}}^{V_{5}} \frac{m \cdot \delta}{\frac{P_{t}}{V_{4}} - m \cdot g \cdot f_{r} - 0.5 \cdot \rho_{a} \cdot C_{x} \cdot A \cdot V^{2}}} dV + \int_{V_{4}}^{V_{5}} \frac{m \cdot \delta}{\frac{P_{t}}{V_{4}} - m \cdot g \cdot f_{r} - 0.5 \cdot \rho_{a} \cdot C_{x} \cdot A \cdot V^{2}}} dV + \int_{V_{4}}^{V_{5}} \frac{m \cdot \delta}{\frac{P_{t}}{V_{4}} - m \cdot g \cdot f_{r} - 0.5 \cdot \rho_{a} \cdot C_{x} \cdot A \cdot V^{2}}} dV + \int_{V_{4}}^{V_{5}} \frac{m \cdot \delta}{\frac{P_{t}}{V_{4}} - m \cdot g \cdot f_{r} - 0.5 \cdot \rho_{a} \cdot C_{x} \cdot A \cdot V^{2}}} dV + \int_{V_{4}}^{V_{5}} \frac{m \cdot \delta}{\frac{P_{t}}{V_{4}} - m \cdot g \cdot f_{r} - 0.5 \cdot \rho_{a} \cdot C_{x} \cdot A \cdot V^{2}}} dV + \int_{V_{4}}^{V_{5}} \frac{m \cdot \delta}{\frac{P_{t}}{V_{4}} - m \cdot g \cdot f_{r} - 0.5 \cdot \rho_{a} \cdot C_{x} \cdot A \cdot V^{2}}} dV + \int_{V_{4}}^{V_{5}} \frac{m \cdot \delta}{\frac{P_{5}}{V_{5}} - m \cdot g \cdot f_{r} - 0.5 \cdot \rho_{a} \cdot C_{x} \cdot A \cdot V^{2}}} dV + \int_{V_{4}}^{V_{5}} \frac{m \cdot \delta}{\frac{P_{5}}{V_{5}} - m \cdot g \cdot f_{r} - 0.5 \cdot \rho_{a} \cdot C_{x} \cdot A \cdot V^{2}}} dV + \int_{V_{4}}^{V_{5}} \frac{m \cdot \delta}{\frac{P_{5}}{V_{5}} - m \cdot g \cdot f_{r} - 0.5 \cdot \rho_{a} \cdot C_{x} \cdot A \cdot V^{2}}} dV + \int_{V_{4}}^{V_{5}} \frac{m \cdot \delta}{\frac{P_{5}}{V_{5}} -$$

where V_1 , V_2 , V_3 , V_4 denote linear speeds at which the maximum engine power can be achieved in gears 1, 2, 3 and 4, respectively.

Vehicle simulation model

The presented formulas are used to model vehicles with various types of powertrain systems. All processes that describe a vehicle's motion have to be taken into account to solve optimization problems.

Research into new powertrain systems in the automotive industry contributed to the development of comprehensive driving simulators, in particular for analyzing the interactions between the system and its individual components (DABADIE et al. 2011, DA COSTA, ALIX 2011), describing the characteristics of various components (HUSAIN, ISLAM 1999), developing and validating control algorithms and vehicle control systems (SCIARETTA et al. 2008, VERDONCK et al. 2010). A driving simulator developed based on the LMS IMAGINE.Lab AMESim® platform (https://www.plm.automation.siemens.com/global/en/products/ simcenter/simcenter-amesim.html) is presented in Figure 1.



Fig. 1. Simulation model of a vehicle developed in the LMS.IMAGINE.Lab AMESim® environment

The specific character of the optimization procedure should also be considered, including iteration algorithms which can perform more than 1,000 individual calculations. Empirically determined characteristics of selected components in a model of a complex mechanical system can be used to reconcile model requirements with research assumptions and the accuracy of the results. In a simulation, the model of an internal combustion engine does not rely on known methods for calculating basic processes (HEYWOOD 1988). Engine parameters in the simulation model were described based on empirical data, including the speed characteristics of an internal combustion engine (GRYTSYUK, VRUBLEVSKYI 2018) and general engine characteristics.

The proposed model has considerable potential for analyzing the influence of structural and operating parameters on a vehicle's energy consumption, engine dynamics and compliance with emission standards.

Selection of driving cycles for the optimization problem

A detailed numerical description of tractive force and linear velocity in realworld driving conditions is relatively complex. Driving cycles that simulate a typical driving environment are developed to best represent real-world conditions. Depending on the aim of the analysis, driving cycles can simulate urban or extra-urban traffic, and they describe changes in the speed of a vehicle moving on a flat roadway. Various driving cycles have been developed for analyzing energy efficiency in vehicles (BARLOW et al. 2009, GIAKOUMIS, ZACHIOTIS 2017).

Until recently, the New European Driving Cycle (NEDC) was the mandatory driving cycle for assessing emission levels in passenger vehicles. The NEDC was developed in the late 1980s, and it does not fully reflect present traffic conditions, mostly due to changes in traffic intensity and the number of vehicles. The NEDC was designed to represent typical urban driving conditions, including idling (GIAKOUMIS, ZACHIOTIS 2017), which largely contributed to the development of start-stop systems. Moreover, the assumed acceleration values did not require high engine loads in modern vehicles, which prompted designers to downsize engines. The cycle was performed on a roller test bench at a temperature of 20-30°C.

The effectiveness of optimization is largely determined by the operating parameters of the powertrain. Vehicle performance is generally assessed in stationary mode or in test cycles. The WLTC driving cycle produces more accurate results, and a vehicle's real-world performance can be simulated with an accuracy of up to 80% (GIAKOUMIS, ZACHIOTIS 2017).

The performance of a four-cylinder 2 dm^3 diesel engine in a class 3 vehicle was compared in the NEDC and the WLTC (Fig. 2), and the results indicate that are engine characteristics are not easy to determine. Unlike in the NEDC, the engine operates in non-stationary mode during the entire driving cycle in the WLTC test. The engine has the following characteristics:

- idling time is 242 s or 15% of the entire test cycle;

 the WLTC involves 6 non-stationary modes during which engine crankshaft speed increases from neutral load or, if the vehicle is equipped with a start-stop system, the engine is shut down and then started;

 instantaneous power momentarily coincides with points in the speed characteristic, which is not typical of the NEDC;

- the portion of the driving cycle when load is limited to 50% of the maximum load and the rotational speed of the crankshaft ranges from 1200 to 3000 rpm can be identified.

Fuel consumption in the WLTC is higher than in the NEDC test, in both older and brand-new vehicles, approximating real-world fuel consumption. In the NEDC, fuel consumption is measured under specific driving conditions,



Fig. 2. Indicated mean effective pressure (IMEP) in a light-duty vehicle (GVW 3500 kg) in NEDC and WLTC tests

such as urban and extra-urban driving. The transition from the NEDC to the WLTC started in 2017, and fuel consumption is currently measured in speed intervals. Different testing speeds and maximum speeds are applied to various vehicle classes. Fuel consumption in the NEDC and the WLTC is compared in Tables 1 and 2.

Fuel consumption in Toyota Yaris

Table 1

Toyota Yaris 1.5			
NEDC		WLTC	
Test conditions	fuel consumption [L/100 km]	speed	fuel consumption [L/100 km]
Urban	6.5	low	7.9
Extra-urban	4.3	medium	5.9
Combined cycle	5.1	high	5.2
_	_	very high	6.1
_	_	combined cycle	6.0

Source: own elaboration based on the manufacturer's specifications.

2	9	8	

Toyota RAV4 2.0				
NEDC		WLTC		
Test conditions	fuel consumption [L/100 km]	speed	fuel consumption [L/100 km]	
Urban	6.8	low	8.9	
Extra-urban	5.4	medium	7.2	
Combined cycle	5.9	high	6.3	
-	-	very high	7.7	
_	-	combined cycle	7.3	

Fuel consumption in Toyota RAV4 SUV

Source: own elaboration based on the manufacturer's specifications.

The compared driving cycles produced different results. The WLTC test has steeper accelerations and higher engine load than the NEDC. As a result, fuel consumption better reflects real-world driving conditions. Regardless of the driving cycle, instantaneous engine torque can be expressed as follows:

$$M_e = \frac{\left(m \cdot g \cdot f_r \cdot \cos\alpha + 0.5 \cdot \rho_a \cdot C_x \cdot A \cdot V^2 + m \cdot \delta \cdot \frac{\mathrm{d}V}{\mathrm{d}t}\right) \cdot r_d}{i_a \cdot i_o \cdot \eta_t} \tag{17}$$

When the change in time is relatively small, it can be assumed that the vehicle moves in linear motion and its acceleration is constant. Instantaneous torque M at any point in the driving cycle can be calculated with formula (17). Depending on speed, instantaneous points in the driving cycle denote the operating region of the powertrain. The relevant information plays a very important role during the development of optimization techniques. Powertrain performance should be maximized at points representing higher loads.

Selection of decision parameters, functional limitations and quality criteria

During optimization, special attention is paid to vehicle dynamics, including acceleration (formula 16) and braking distance (FRIES et al. 2018, GILLESPIE 1992, LI et al. 2020, WALIGÓRSKI, KUCAL 2018). A set of dynamic indicators can be used to establish quality criteria as well as functional limitations in the optimization problem.

OGLIEVE et al. (2017) proposed an effective analytical procedure for calculating fuel consumption based on the NEDC speed profile. The analysis involved

Table 2

an integrated optimization procedure to minimize fuel consumption and NO_x emissions as objective functions. Optimal gear ratios were determined for 4-, 5- and 6-speed gearboxes as control parameters in the optimization process. In the analysis, the gear shifting strategy should be determined by minimizing one of the declared objective functions. In the best case scenario, fuel consumption is reduced by 7.5% and NO_x emissions are reduced by 6.75% in a 6-speed gear box where the gear shifting strategy is based on minimal fuel consumption for a given engine type. These results indicate that gearbox optimization is an effective and cheap method of reducing fuel consumption and harmful emissions.

The appropriate optimization technique should be applied in the process of vehicle modernization. In the bus presented in Table 3, the gear ratio was modified when a spark-ignition engine was replaced with a diesel engine, as recommended by the manufacturer. Spark-ignition and diesel engines have different characteristics (HEYWOOD 1988), and a vehicle's gear ratio has to be adapted accordingly. The effects of different gear ratios on fuel economy, emissions and engine dynamics are well known. A multi-criteria optimization technique can be applied to make a trade-off between the above parameters.

Technical specification of a light-duty vehicle (LDV) RUTA-25d Specification (GRYTSYUK, VRUBLEVSKYI 2018) Vehicle dimensions [mm] 7000/2050/2730 Axle width [mm] 3745Tire size 232/65 R16 1900/1600 Gross vehicle weight rating/curb weight [kg] Acceleration 0-100 km/h [s] _ 130Maximum velocity [km/h] Average fuel consumption [l/100 km] 19.5Maximum output [kW/rpm] 88.3/3200 Rated torque [rpm] 3200 297/1600-2700 Maximum torque [Nm/rpm]

Research methodology for optimizing vehicle design

Vehicle design can be optimized with the use of the following strategies or their combinations (VRUBLEVSKYI, WOJNOWSKI 2019):

- Design of Experiments (DoE) methods (Ross 1998). These methods facilitate the selection of the optimal solution. However, the DoE approach may

Table 3

produce unsatisfactory results, in particular when only one criterion is selected. Various sampling methods can be used in the DoE approach, including orthogonal arrays, Sobol sequences (SOBOL, STATNIKOV 2006) and Monte Carlo methods (RUBINSTEIN, KROESE 2008);

– optimization methods. Various optimization methods have been proposed. The selection of the appropriate optimization algorithm is a very important consideration because some optimization methods have been designed for specific purposes, depending on spatial parameters (spatial modality, continuity, linearity, etc.).

The effectiveness of these methods increases when they are applied in combination. For example, the first method can be used to plan the experiment, test the boundary values of the analyzed parameters and establish a set of decision parameters. Ultimately, the appropriate optimization method is used to identify the optimal point. In this case, the search for the optimal solution does not begin from zero or in a random manner. The DoE approach is used at the beginning of the optimization process to determine initial search conditions. The optimization problem described in this study was solved with the use of Simcenter Amesim 2019 software (DABADIE et al. 2017, LE BERR et al. 2012, LI et al. 2020).

Optimization process

Parameter space analysis in a vehicle with an internal combustion engine

The relationships between gearbox parameters and selected quality criteria, i.e. fuel economy and acceleration, was examined with the use of DoE methods to determine the boundary values of the investigated parameters. The results obtained in this stage of the analysis can be used to narrow down the search space for localizing the global optimum. The relationships presented in Table 4 were determined by calculating sampling points whose input vectors were described with the Monte Carlo method. The values of all parameters had normal distribution. The obtained data were used to analyze the influence of gearbox parameters on selected performance parameters. When the influence of the 2nd and 4th gear ratio on fuel consumption was analyzed, significant differences were noted only for the 4th gear ratio. The system was not sensitive to the 2nd gear ratio. In turn, an analysis of the 3rd and 4th gear ratios revealed that both variables influenced fuel economy.

Sobol sequences were used to derive input parameter vectors for the sampling points, presented in Figure 3. The results of the calculations for each sampling point are localized in the plane of fuel economy criteria – difference in acceleration.

Table 4



Fig. 3. Sampling points in the space of decision criteria for fuel consumption and the dynamic performance of a vehicle with an internal combustion engine

Trade-off solutions can be identified in the resulting set of solutions, and they are located on the Pareto optimal curve. These points describe the best combination of input parameters, i.e. gear ratios whose implementation contributes to reducing fuel consumption or improving engine dynamics.

Multi-criteria optimization of gearbox parameters

The use of DoE tools in data analysis supports the development of an appropriate set of input parameters in the optimization process the selection of boundary values of decision parameters and quality criteria, as well as the selection of the initial point for localizing the optimum. Two criteria were selected for solving the optimization problem where the Non-Linear Programming by Quadratic Lagrangian (NLPQL) algorithm was used to upgrade the gearbox in a vehicle with an internal combustion engine:

- fuel consumption per 100 km;
- distance traveled during the simulation.

The first criterion was selected on the assumption that the goal of optimization is to reduce fuel consumption during the simulation. The second criterion was adopted to accurately reflect changes in the vehicle's speed based on the speed profile of a given driving cycle. The total distance traveled by the vehicle during the test was compared. The longest distance was indicative of the highest average speed and, consequently, the smallest deviations in linear speed relative to the adopted speed profile.

The results of the optimization procedure for the NEDC and the WLTC are presented in Table 5. When the gearbox was not adapted for use with a diesel engine, fuel consumption was lower by 1 L in the NEDC than in the WLTC. The same difference was noted when the optimization problem was based on fuel consumption only, with a minor decrease in absolute values. The correlation between qualitative variables was maintained when two criteria were applied in the optimization process. Minimal fuel consumption was achieved in the NEDC test (9.97 L/100 km).

Table 5

Fuer consumption [1, 100 km] in a venicle with an internal combustion engine			
Cycle	Before optimization	Criterion: fuel consumption	Criteria: fuel consumption and distance
NEDC	10.1885	10.1633	9.97
WLTC	11.6086	11.3575	11.2493

Fuel consumption [L/100 km] in a vehicle with an internal combustion engine

Dynamic engine performance is also highly desirable in vehicles. Therefore, the optimization procedure was based on the time required to achieve a given linear speed. The input parameter was the difference between the final velocity after 45 seconds of acceleration and the test velocity of 25 m/s. The minimum value of the above difference was used to set decision parameters. In this analysis, the decision parameter was the gear ratio. Changes in the vehicle's test velocity, the final velocity and the differences between these values are presented in Figure 4.



a – before optimization, b – after optimization

The difference in final velocity after optimization was 0.16131 m/s. The gear ratios for each gear were determined at: $i_g = 4.11$; $i_1 = 3.34$; $i_2 = 2.32$; $i_3 = 1.49$; $i_4 = 1.03$; $i_5 = 0.813$.

It should be noted that the NLPQL algorithm is not the only method for solving an optimization problem. When a multi-objective genetic algorithm (GHORBANIAN et al. 2011, MIRJALILI 2019, URBINA CORONADO et al. 2018) was applied to the same decision parameters, a small difference was observed in the values of quality criteria and parameters (Tab. 6). However, an analysis of the results indicates that the NLPQL generated lower values of fuel consumption and CO and NO_X emissions; therefore, it appears to be better suited for solving the presented optimization problem (Tab. 6).

Comparison of optimization results			
Parameter/Criterion	Base	NLPQL	Genetic algorithm
$1^{\rm st}$ gear ratio (i_l)	2.8	2.8	2.8
2^{nd} gear ratio (i_2)	1.7	1.7	1.7
$3^{\rm rd}$ gear ratio (i_3)	1.25	1.25	1.307
4^{th} gear ratio (i_{4})	0.9	1.026	1.00
$5^{\rm th}$ gear ratio (i_5)	0.813	0.813	0.797
Fuel consumption [g] WLTC	1383	975	985
CO emissions [mg] WLTC	150.6	119.9	119.3
HC emissions [mg] WLTC	17.61	14.45	14.49
NO _x emissions [mg] WLTC	60.67	35.38	36.00

Table 6

Conclusions

Optimization techniques have to be applied in the process of designing new vehicles and modernizing the existing solutions. Optimization techniques reduce the time and cost of such operations and facilitate the search for trade-off solutions that account for different and often contradictory customer requirements as well as vehicle operating conditions.

This study demonstrated that the effectiveness of the optimization process is determined by the operating conditions of the powertrain. The accuracy of the results can be improved under the conditions prescribed in the WLTC test. A comparison of the optimization results for a vehicle with an internal combustion engine revealed that when the gear box was not adapted for use with a diesel engine, fuel consumption was 1 L lower in the NEDC than the WLTC test. The same difference was noted when the optimization problem was based on only one criterion, i.e. fuel consumption, with a minor decrease in absolute values (10.1633 L/100 km and 11.3575 L/100 km). The correlation between qualitative variables was maintained when two criteria were applied in the optimization process. Minimal fuel consumption was achieved in the NEDC test (9.97 L/100 km).

The criteria for selecting powertrain parameters in a vehicle with an internal combustion engine were fuel economy, engine dynamics, and toxic emissions. When a vehicle with an internal combustion engine was optimized with the involvement of the NLPQL algorithm and the genetic algorithm, only minor differences were noted in the values of quality criteria and parameters. The NLPQL algorithm generated lower values of fuel consumption and CO and NO_X emissions.

The results of this study indicate that optimization techniques can be used to adapt the powertrain to different types of engines by modifying parameters such as the gear ratio. As a result, vehicle parameters can be more accurately tailored to specific user needs and requirements. Gearbox parameters can be accurately adapted to a specific route and terrain by incorporating GPS data and the speed profile in a driving cycle and using real-world road gradients in the simulation model, in particular in the process of modifying the design of municipal buses.

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