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Energy Efficient Drive Management of Lightweight Urban Vehicle

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In this paper, the energy saving effect of optimized driving strategy is presented and compared to human driving strategy. The driving strategy of a one-seated experimental electric vehicle is investigated and optimized in this study, where the objective function of optimization is the minimization of the consumed energy. Measurement-based vehicle model is used during the optimization process. The initialization and constraints of optimization are set up by analyzing the acquired vehicle data of the driver. The analyzation is done using a transform algorithm, making the initialization of optimization automated. Genetic algorithm is used with mixed initial population acquired from measured driving data and from creation function. Using this hybrid initial population helped to decrease the time of optimization. The resulted velocity profile of the optimized driving strategy was used in field test measurements, where 4.28% energy savings was achieved compared to the results prior to optimization.

1. Introduction

Vehicle operation is key to energy efficiency and reduction in fuel consumption and greenhouse gas emissions (Chuah et al., 2022). The environmental impact of urban transportation can be reduced by proper vehicle management. The benefits of growing use of electric vehicle (EV) in urban areas is unquestionable. This effect can be further boosted by Dynamic Wireless Power Transfer (DWPT) technology, which would help the reducing of local air pollution and related externalities. (Lazzeroni et al., 2021). The spreading EVs is also supported by car sharing services as EV is ideal for operation in cities, where these services aim to work. Mounce and Nelson (2019) highlights the connection and potential in mobility systems and described how urban region can benefit from the transition from conventional to EVs and the car-sharing services accelerating the spreading of EVs. Kolbe (2019) analyses the impact that the replacement of conventional vehicles with alternative (EVs) has on summer heat island intensity (SHII) and CO_2 emission, the study highlights that SHII, and CO_2 levels are reduced by electric and hydrogen vehicles that are powered by renewable energy. The environmental and consumption benefit could be enhanced further by utilizing the efficiency of the EV’s powertrain by optimizing the vehicle operation. The vehicle efficiency is depending on the applied velocity profile of the given track, which means the optimization of vehicle’s velocity profile means increasing vehicle efficiency and decreased fuel consumption and emission. The methodologies of determining energy optimal velocity profiles for vehicles has been researched from many aspects. Saerens at al. (2013) discussed the calculation methodologies of optimal velocity profile for internal combustion engine vehicles, where the Pontryagin’s maximum principle was used for calculation to eco-cruise controller for 5% of fuel save. Based on the principles of velocity profile optimization optimal control and energy-efficient driving problems were investigated in Sciarretta et al. (2015), where general analytical formulation for internal combustion engine vehicles and electric vehicles were presented. Beside mathematical formulation, the relevance of this topic could even be extended by appearance of smart vehicles. The energy efficiency of road transportation could even get higher by utilizing the facilities of vehicle-to-vehicle (V2V) or vehicle-to-infrastructure (V2I) communications. Jan et al. (2021) proposed method, where speed trajectory is generated by eco-driver model for connected and automated vehicles (CAVs), the presented simulations resulted in 14.5% fuel consumption saving. The tools and possibilities are given to determine better drive management for EVs. In this study, the optimization process and energy saving effect of properly determined driving strategy is highlighted.

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2. Driving strategy determination

The efficiency of vehicle operation is determined by the vehicle's velocity profile applied on the investigated track, which can be chosen by the driver or specified as the result of optimization process. In this paper, an energy-efficient urban vehicle was used for the experiments. The setup can be easily modified, and the associated vehicle model can be structured. The vehicle components need to be identified and modelled to simulate the exact behavior of the vehicle. Vehicle modelling can be performed in several ways. Since a vehicle is designed for energy efficiency competition, even minor simplifications can lead to higher degree of inaccuracy in the model. Grey-box modelling approach was used to minimize the model errors and take all the factors into account, which are usually neglected in analytical models. The unique vehicles characteristics and extreme low weight (165 kg) also explains the need of this modelling approach. The vehicle under study (Figure 1) won the Shell Eco-marathon Battery Electric Urban Concept category in Assen, the Netherlands in 2022, which is the world's largest energy efficiency competition for concept vehicles. Figure 1 depicts the moments of resistance measurements, where the connections of the body panels were taped, as it is standard practice in the competition.

Figure 1: SZEmission - during vehicle resistance measurement

The coast down test is used to determine the vehicle's resistance, which means having the resistance forces as a function of vehicle speed. Another important component to be modelled is the powertrain, which is also not determined by analytical models of the electric machine but identified by test bench measurements. In this way, beside the losses of the gearbox and motor controller, all the other losses occurring in the powertrain operation are included in the model. The model determines the efficiency of the powertrain as a function of vehicle speed and driven torque, which is calculated from the electrical and mechanical power consumption during measurements. Actual track information is also important, as the resistance model considers the cornering radius and the elevation of track, the easiest way to map the track model is to use measured or publicly available GPS data.

Once the vehicle model is created, the behavior of the vehicle is described on the given track and the control is done by torque reference command. This reference is processed by the motor controller and the powertrain produces torque based on this command, this torque is converted to traction force, which is accelerating the vehicle against resistance forces. The vehicle's velocity profile is product of the torque reference, eventually determining its operation. In the presented model the optimization of velocity profile means the optimization of torque reference. During the validation phase field test measurements are performed, where optimization and vehicle model are both checked. The main task is the comparison of optimization results to the driver data and verification of the model's energy consumption. The flowchart of driving strategy determination is shown in Figure 2.

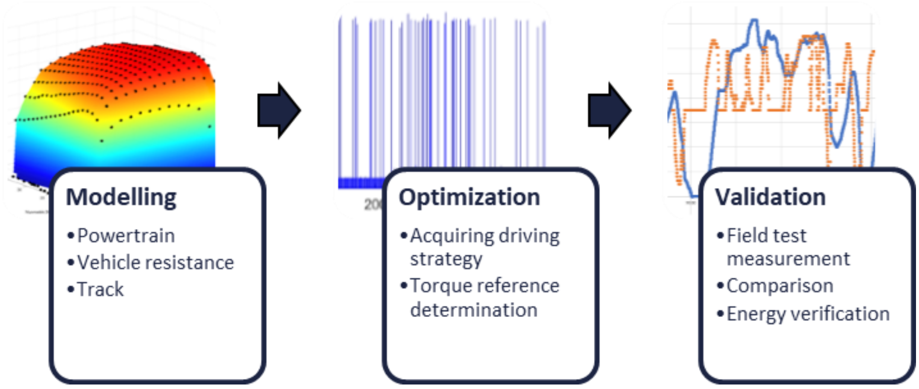


Figure 2: Flowchart of Driving Strategy determination

3. Formulation of Optimization Problem

The determination of driving strategy for energy efficient road vehicle was also studied by Sawulski and Ławryńczuk (2019), when investigated the control strategy of an internal combustion engine prototype vehicle dedicated for Shell Eco-marathon. The results showed the effectiveness of evolutionary optimization methods, while traditional optimization strategies were shown to be hardly applicable. In this work, classical genetic algorithm (GA) is used for optimization in MATLAB environment. The fitness function is defined in Eq(1), where the consumed electric energy is represented E, the generated traction force F_{trac}, vehicle speed v, and the efficiency of powertrain in the actual operating point η_{drive}.

$$minimize\ E = \int_0^T F_{trac}(t)\ v(t)\ \eta_{drive}(t)\ dt \tag{1}$$

The consumed electric energy is the outcome of the simulation carried out on the vehicle model with the currently applied torque reference. It means that the GA employs the simulation model during each iteration to provide input for fitness function evaluation. The optimization problem was formulated according to Max Torque optimization. Max Torque optimization method utilizes the acceleration-coast down technique to the given track to find the appropriate position of acceleration (Pusztai et al., 2022). The torque values are maximized by the available physical limit, which is controlled by the powertrain subassembly of the vehicle model. Optimization constraints were set up to ensure the completion of the lap in time, it was formulated according to Eq(2).

$$\begin{gathered} s_{max} - 2 \leq \int_0^T v(t)\ dt \leq s_{max} \\ T \leq T_{max} \end{gathered} \tag{2}$$

The simulated lap time (T) and lap distance (s) were defined in Eq(2) to have comparable results within tight calculation margin. The vehicle speed was forced to be 0 km/h by the model, when either of the constraints of Eq(2) reached, this emulated the usage of hydraulic brake, the application of regenerative braking was avoided to simplify the optimization problem. The duration of the optimization is depending on the number of variables (n) and from the permitted values of the parameter vector. In case of Max Torque optimization, the implementation of the parameter vector is described in Eq(3-5). For practical reasons, the number of variables is defined according to track length as proposed in Eq(3). The optimization parameter vector denoted by z, contains the position of torque application to the corresponding s_i vector, which is track length dependent.

$$n = \frac{s_{max}}{10} + 1 \tag{3}$$

$$s = (s_0, s_1 \ldots s_{n-1}) \quad s_i = i \cdot 10 \quad (i = 0, 1 \ldots n\text{-}1) \tag{4}$$

$$z = (z_0, z_1, \ldots z_{n-1}) \quad z_i = \begin{cases} 0, & if M_i = 0 \\ 1, & if M_i = M_{max} \end{cases} \tag{5}$$

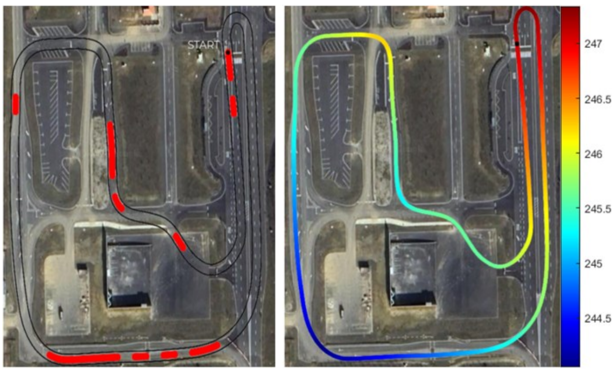
The investigated track was selected in ZalaZone proving ground at the Smart City Zone platform, which is mainly dedicated for investigation of autonomous vehicles, but provides proper conditions for analyzing drive management in urban environment. The designated track length is 865 m, which needs to be completed in 130 seconds.

The result of optimization is majorly dependent on the formulation of the optimization problem, but also the optimization properties are important. In the presented optimization hybrid initial population was used since it was partly acquired from measured driving data, this was combined with the result of the creation function of GA. This process was done by applying a transform algorithm, which evaluates the attempts of human driver and converts it to applicable driving pattern for the optimization environment. The resolution can be adjustable to control the variable number. Linear interpolation is used to make equidistant points in the parameter vector according to the resolution. The average run time of simulation and evaluation of fitness function is approximately 0.4 s, the total run time of optimization can be based on the function count value. Two separate optimization case was set up with the same problem formulation to compare the effectiveness of application of hybrid initial population. The results of attempts are summarized in Table 1.

Table 1: Comparison of optimization results with different initial populations

	Normal	Hybrid
Variables	88	88
Number of Initial Population	200	200
Human Driving Pattern	0	8
Function Count	20,486	17,366
Generations	104	88
Run Time (second)	8,195	6,947
Best individual	16,502 J	16,151 J

From the results it is clearly visible that the hybrid attempt provided better result (2.1%) in less time, which confirms the serviceability of this method. It is important to note that the solution of GA cannot be considered global optimum as nondeterministic processes such as selection, mutation, and crossover are applied to generate a population of candidate solutions from the initial population. It is advisable to create more optimization attempts to overcome of the risk of being stuck in local minima, where also the application of hybrid population could help. The result of hybrid optimization attempts was used as reference value for field test measurements. In Figure 3a, the acceleration points are visualized as red dots in the designated track in Smart City Zone according to the optimization results using Max Torque method. In Figure 3b the altitude of the track is demonstrated, it is interesting to note the relation of changes in altitude and acceleration points. The optimization utilizes the characteristics of the track to ensure improvement in the resulted driving strategy.



(a) (b)

Figure 3: Results of optimization (a) places of torque applying and (b) altitude of designated track in Smart City

4. Field test results and discussion

The hybrid initial population was acquired from field tests and the validation of optimization results also need to be done at the track. During the process of validation of predetermined velocity profile is displayed for the driver, who tries to follow the pattern and the position of torque application. The handling of torque is done by pressing button, which applies the physically available maximum value, this method enables the driver to handle the vehicle properly and control the acceleration timing. This method was also used in the comparison test before, the only difference is that the driver has the strategy to follow during driving. To avoid the effect of external circumstances the applied driving pattern was sampled with the previously used transform algorithm and the gathered results was compared in vehicle simulation environment. The velocity profile (Figure 4a) and energy consumption (Figure 4b) from the best valid attempts is shown from each simulation case.

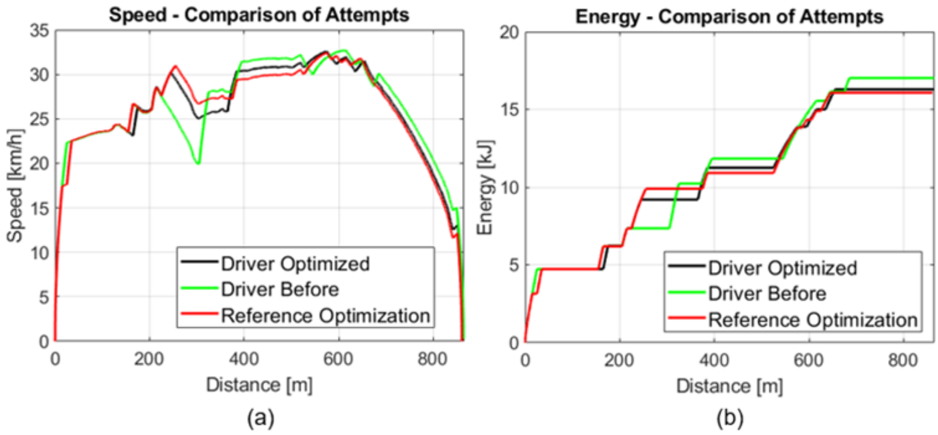


Figure 4: Test results of (a) vehicle speed and (b) energy consumption

The correlation of the red and black curve is eye-catching, both in the speed profile and in energy consumption. The illustrated curves describe efficiency and importance of driver assistant display. Detailed comparison is summarized in Table 2, where 8 laps before the optimization and 8 laps after applying the result were analyzed.

Table 2: Driver attempts before and after optimization

	Driver Before	Driver Optimized
Best attempt	17,018 J	16,290 J
Energy difference	867 J	139 J
Difference to reference	5.09 %	0.85%
Variance in energy (s^2)	854 J	286 J
Valid attempts ratio	87.5%	62.5%

The optimized driving strategy meant 5.09% improvement in energy consumption during 1 lap compared to the best attempt of the driver before the optimization. The driver could achieve 4.28% improvement after following the defined driving strategy and could approach the theoretical maximum with 0.85% accuracy. It is worth mentioning that the theoretical maximum is the result of optimization, while the driver optimized best attempt is the result of field test measurement. In this case the human driving error was just 0.85%, while only 62.5% of the laps were valid. The cause behind these statistics is that the optimization fully utilizes the time, while it is hard task for a human driver and in majority of cases the driver was out of time, making attempts invalid. This was not a problem before optimization, because the driver put more emphasize to make the attempt valid, but the driving strategy was different lap by lap. The difference between the applied driving strategies before the optimization can be characterized by the variance in energy consumption during the laps. Before the optimization the variance was 854 J, while after it was only 286 J (66.5% decrease), which means that the driver concept was clear and followable. Driving errors can be corrected by experience, only the weather conditions cannot be influenced, but they have major effect of the driving, especially the wind. In that case, the driver should have the knowledge of the vehicle and experience to modify the predetermined strategy to keep the time and make valid attempts.

5. Conclusion

In this work, the process of driving strategy determination of a lightweight urban vehicle was presented. The vehicle model was set up as the first step of the process, where measurement-based vehicle model was used. This way the inaccuracies can be minimized, although it is handled grey box type model. In the next step the optimization framework needs to be defined, by formulating the optimization problem and constraints. In this study genetic algorithm was used to solve the optimization problem, which was designed to find positions of accelerating in the track according to the defined Max Torque method. During the initialization of optimization, two separate cases were compared. In the first case, the initial population was fully created by the creation

function, while in the second case it was combined by human driving data acquired from previous field test. Hybrid initial population was created this way.
After the solution the applicability of this hybrid initial population was verified as the running time was less and the solution was 2.1% better than in the normal case. This solution was considered as reference in the validation phase, which was made in the ZalaZone proving ground Smart City Zone platform in the designated track. The validation process aims to approve the feasibility of optimization result and compare its effectiveness to the human driver. The driver was supported by the display of the optimized driving strategy as a reference.
The results of validation showed that after the optimization the energy consumption was decreased by 4.28% and the energy consumption variance between the laps by 66.5%. This clearly shows the effectiveness of the presented method, although keeping the time limit is still hard task for the driver, which requires experience. In the future work, the effects of weather condition such as wind speed is planned to be considered to make the optimization process more suitable and widely applicable.
The proper driving strategy has extensive effect on the energy consumption and emissions. The implementation of optimized driving strategies especially with the expansion of smart vehicles, has the potential to further enhance energy savings in urban transportation, leading to a reduction in global CO_2 emissions.

Nomenclature

CAV – Connected and Automated Vehicles
CO_2 – Carbon dioxide
DWPT – Dynamic Wireless Power Transfer
E – energy, J
EV – Electric Vehicle
F_{trac} – traction force, N
GA – Genetic Algorithm
M – applied torque, Nm
M_{max} – maximal applied torque, Nm
n – number of variables, -
s – lap distance vector, -
s^2 – sample variance, -
SHII – Summer Heat Island Intensity
s_{max} – total lap distance, m
T – simulation time, s
T_{max} – maximum of simulation time, s
v – vehicle speed, km/h
V2I – Vehicle-to-Infrastructure
V2V – Vehicle-to-Vehicle
z – optimization parameter vector, -
η_{drive} – powertrain efficiency, -

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