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Vehicle Model for Driving Strategy Optimization of Energy Efficient Lightweight Vehicle

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The energy consumption and CO_2 emission of urban vehicles are highly dependent on their operation. Vehicle models can be used for optimizing driving strategy for emission reduction. This paper proposes a novel vehicle model of a one-seat electric vehicle dedicated for Shell Eco-marathon (SEM), the most famous and largest race of energy efficient vehicles. The available vehicle dynamical formulas cannot be directly used to describe the characteristics of lightweight vehicles. In the current work, a novel grey-box vehicle model has been introduced, based on measurement scenarios. The whole model has been elaborated in MATLAB Simulink environment, where individual subassemblies were defined for driving resistance model, powertrain model, and the racetrack characteristics. The resistance force model manages the forces in straight line moving and also takes the effect of cornering into account. Based on test bench measurements the complete efficiency map of the drivetrain was created and implemented into the vehicle model. The presented vehicle model is suitable for driving strategy optimization. By optimizing this model, 7.1 % energy savings have been achieved compared to best human driven lap. Driving strategy optimization will be essential, especially for autonomous vehicles, expressing the importance of the presented results in the future.

1. Introduction

The popularity of electric vehicles is increasing and its potential in terms of the reduction of CO_2 emission is underestimated (Hoekstra, 2019) especially in urban environments. Nowadays, it is technically achievable to replace 72.3 % of the fossil fuel demand in the transportation to electricity. Due to this transition and the higher energy efficiency of electrically driven transportation, the final energy demand could be decreased by 50.6 % (Dominković et al., 2018). Alternative powertrains and using of lightweight materials are also viable ways to reduce energy consumed and CO_2 emission (Palencia et al., 2012).

Experimental lightweight electric vehicle of the Széchenyi University was developed in 2019 for participating in the Shell Eco-marathon (SEM), which is one of the leading student engineering competitions in the world. The goal of this event is to finish the race with self-developed cars using the least amount of energy. The urban concept vehicles have to complete 10 laps on the given race track, making a full stop at each lap. Vehicles need to cover approximately 16 km in less than 40 min. The minimum driver weight for the one-seat urban concept vehicles is 70 kg. The race scenario was made to imitate urban transportation, where low travelling speeds and frequent stops are usual. The developed battery electric urban concept vehicle, named SZEmission (see Figure 1) was investigated in this article. Field tests were carried out to determine the dynamical response of the vehicle. The detailed measurements allow fine calculation of resistance forces in different drive conditions. Test bench measurements were performed to identify the electric drivetrain. The presented vehicle model also contains track model, which provides input for driving resistance subassembly. The methodology of making measurement-based vehicle model and the detailed subassemblies are presented in the following sections.

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Figure 1: SZEmission - custom built energy efficient lightweight vehicle developed at Széchenyi University

2. Mathematical model of the vehicle

The driver behaviour has general impact on energy utilization of electric vehicles. The eco-driving can be achieved by using energy efficient driving strategies (Bingham et al., 2012) following the optimized drive cycle for the given vehicle path. The driving cycle is determined by the corresponding velocity profile, that can be obtained by solving an optimal control problem (OCP), where the minimization of the consumed energy is the optimization objective (Sciarretta et al., 2015). Often, eco-driving problems are focusing on vehicle components, while the characteristics of the track, especially the corners are also important. The results presented in Becker et al. (2020), clearly showed that energy losses in cornering should not be neglected. This was further investigated in Padilla et al. (2020), where kinematic bicycle model was used to determine eco-driving strategy, including cornering effect for electric vehicle in urban scenarios. The importance of terrain variables was investigated in Yoo et al. (2021), where route search algorithm was used to find energy efficient alternative route for electric vehicles. In this paper, measurement-based vehicle model is proposed for driving strategy optimization.

At first, the basic principles of the longitudinal vehicle dynamics need to be defined according to Eq(1).

$$ma(t) = F_{trac}(t) - F_{res}(t) \tag{1}$$

where m and a represent the mass and the acceleration of the vehicle respectively. The $F_{traction}$ is the total traction force, which accelerates the vehicle against the F_{res} cumulative resistance forces. The formula is shown in Eq(2).

$$F_{trac} = \frac{T_{drive}\, i_{gear}\, \eta_{drive}}{R_{wheel}} \tag{2}$$

The actual traction force can be obtained from a powertrain subassembly, which is fully set up based on test bench measurements.
The resistance forces can be calculated using Eq(3).

$$F_{res} = F_{air} + F_{rolling} + F_{grade} + F_{inertia} \tag{3}$$

The resistance forces are rather different in straight moving and in cornering, thus the vehicle model needs to handle the switching between those operation modes. While traditional modelling methods provide solid accuracy in straight moving, the changes of vehicle parameters during cornering (drag coefficient, rolling resistance due to tire deformation) cannot be formulated this way. At this point it is recognizable that numerous vehicle parameters need to be known exactly to obtain the resistance forces in cornering with reasonable accuracy. Literature is not providing complete models for describing the investigated lightweight vehicle, therefore other methods need to be applied. In this paper systematic approach of creating a grey-box vehicle model is proposed. The model is suitable for solving optimization problems of eco-driving for full track, including the effects of cornering. Based on this approach, the proposed grey box vehicle model is shown in Figure 2.

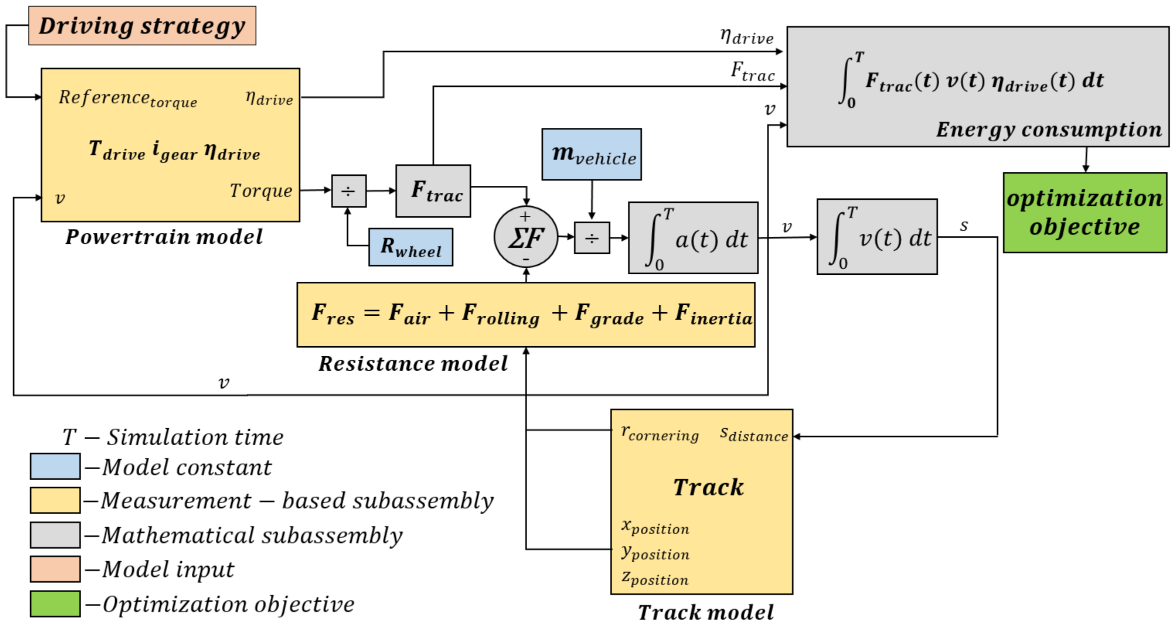

Figure 2: Proposed vehicle model for driving strategy optimization for energy saving purposes

3. Measurement based mathematical modelling

The proposed vehicle model contains three important subassemblies, which can be determined based on systematic measurements. For vehicle identification the powertrain model and resistance model need to be set up, while the vehicle independent track model could vary. Laboratory tests and field measurements were combined to create these subassemblies. The model is implemented in MATLAB Simulink environment, where user defined functions and measurement-based look-up-tables are operating simultaneously according to Figure 2.

3.1 Powertrain model

The vehicle is equipped with self-designed PMSM and motor controller, the torque is transmitted through synchronous belt connection to the left wheel. Various gear ratios ranging from 2.7 to 4 can be applied. The powertrain model has to contain complete efficiency map of the drive, which means that the PMSM, controller, and transmission model have to be combined together. Unique powertrain model was defined for all combination of drive elements (PMSM-controller-transmission). The efficiency map of the complete powertrain was created by measuring the dissipated electric power and provided mechanical power by the powertrain according to Eq(4).

$$\eta_{drive} = \frac{\int_0^t M(t)\omega(t)dt}{\int_0^t U(t)I(t)dt} \tag{4}$$

3.2 Resistance model

Resistance model includes all factors and forces, which decelerate the vehicle, while it is in motion. The model is made by combining the occurring resistance forces in straight moving and during cornering. These two scenarios were investigated separately. In both cases the resistance forces are not divided into components, because the vehicle model uses cumulative effect of them. The resistance forces in straight moving can be calculated from the deceleration data collected from free-rolling tests. During free-rolling test the vehicle is accelerated to a given speed (in the investigated case it is 40 km/h) in straight line and the velocity profile is recorded, while it is slowing down and stops completely. Being aware of the vehicle mass and deceleration, the cumulative resistance forces can be calculated by Eq(5).

$$ma_{deceleration}(t) = F_{res}(t) \tag{5}$$

The free-rolling tests were made back and forth and averaged to eliminate the slope of the track. It is more complicated task to define the resistances during cornering, than in straight moving. Field test scenarios were designed to completely cover the operating range of the vehicle. Cornering radius higher than 200 m is considered to be straight moving, as no significant difference was observed in resistance. The vehicle speed was controlled by real-time speed controller (PI), while the pilot manually followed the designated route. The traction force was calculated from the previously defined powertrain model. The occurring resistance force equals to the traction force as the system is steady. This force can be assigned to discrete cornering radius – vehicle speed data pairs. The cornering resistance was not considered to be symmetric, turn direction sensitivity was assumed based on the unique vehicle structure, so all cornering measurements were made clockwise and anti-clockwise as well. All tests were carried out with 5 bar tire pressure, which is also applied during the race.

Table 1: Field test scenarios for resistance model identification

Vehicle motion state	Attempts	Speed [km/h]	Cornering radius [m]
Straight moving	8	[40]	-
Cornering	2	[5-10-15]	8
Cornering	2	[5-10-15-20]	15
Cornering	2	[5-10-15-20]	30
Cornering	2	[5-10-15-20-25-30]	45
Cornering	2	[5-10-15-20-25-30-35]	60
Cornering	2	[5-10-15-20-25-30-35]	100

3.3 Track model

Track model contains all geometric parameters (position *x[m], y[m], z[m])* of the planned route, cornering radius can be obtained from that data. The track model has been determined by GPS measurements. Vertical force component is also calculated according to height information of track model and transferred to the vehicle resistance model.

4. Model implementation based on measurement results

The powertrain measurements were carried out on custom built electric test bench. Each efficiency map was created using measured data from 315 different operating points, linear interpolation was applied to extend for all reachable operating states of the powertrain. The complete drive efficiency model of the powertrain is shown in Figure 3.

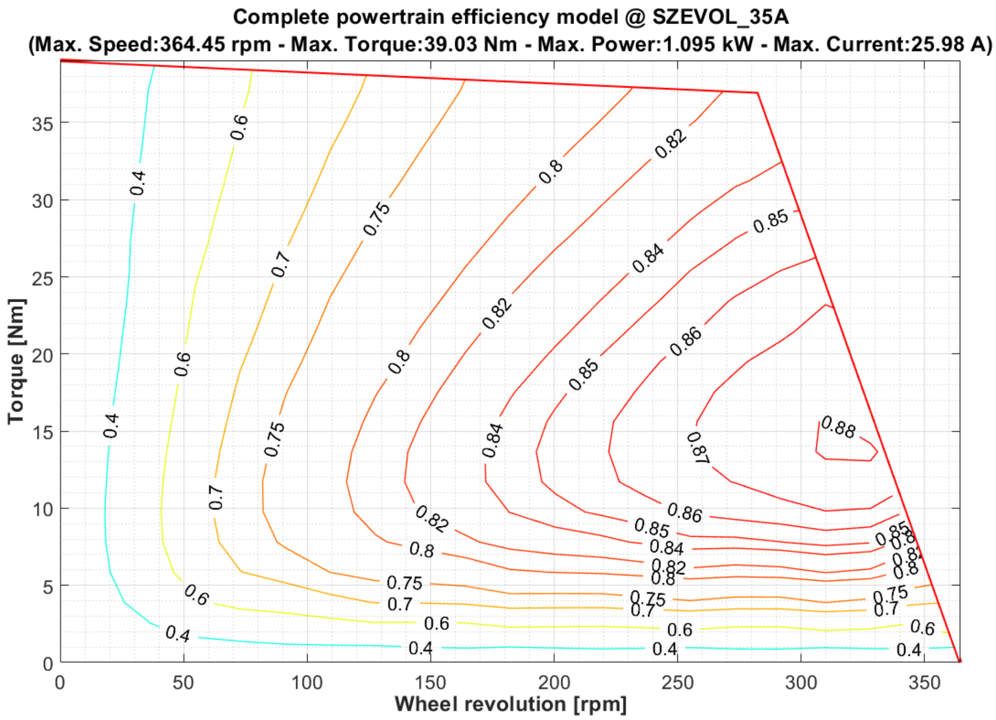

Figure 3: Complete electric powertrain model of SZEmission: trajectories with the related efficiency

The complete resistance force model is described as a surface, which has 3 dimensions: cornering radius, velocity and resistance force. This surface is limited by a 5th grade polynomial acquired from the averaged free rolling tests. This polynomial describes all resistance force components in straight moving. The surface between the polynomial is defined by the force measurement from cornering radius field tests. Curve characteristics of cornering radius measurement is shown in Figure 4, where the traction force is equal to the arising resistance force in case of constant speed control. The track had a ~1° slope, so the form of traction force curve is sinusoidal, the baseline of sinus needs to be found, where the traction force can be determined at measured speed. Manual evaluation was applied due to the unique nature of the measurement. Linear interpolation was applied to compute the whole surface between the measured data sets. The created model is shown in Figure 5. In the current model, the cornering radius cannot be less than 6 m, since it is the physical limit of the vehicle.

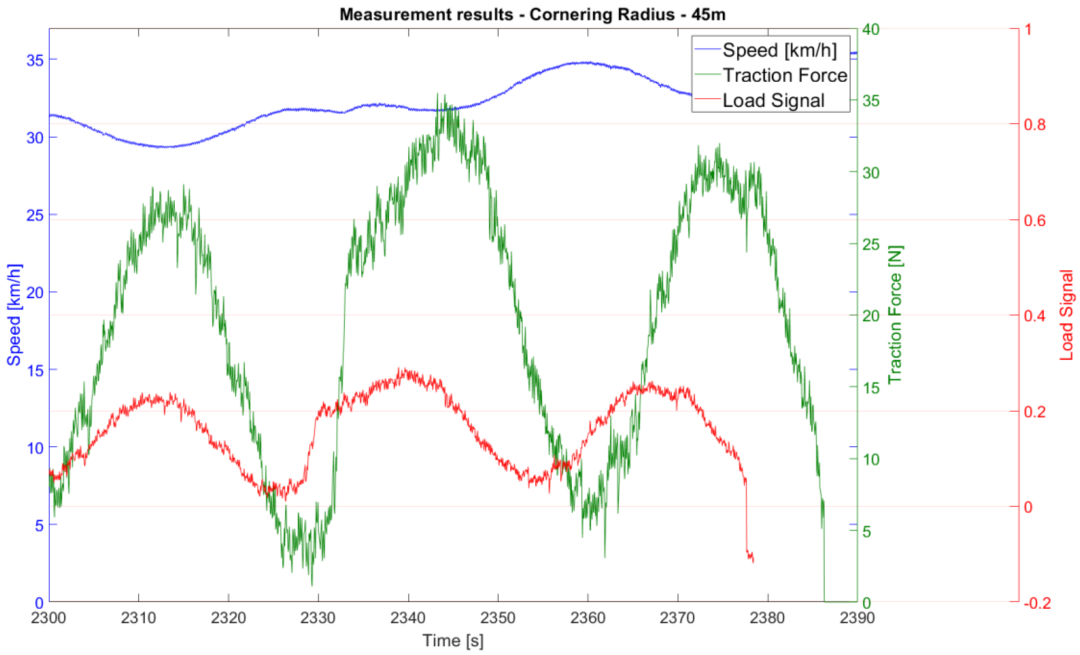

Figure 4: Example of cornering resistance determination in case of cornering radius of 45 m

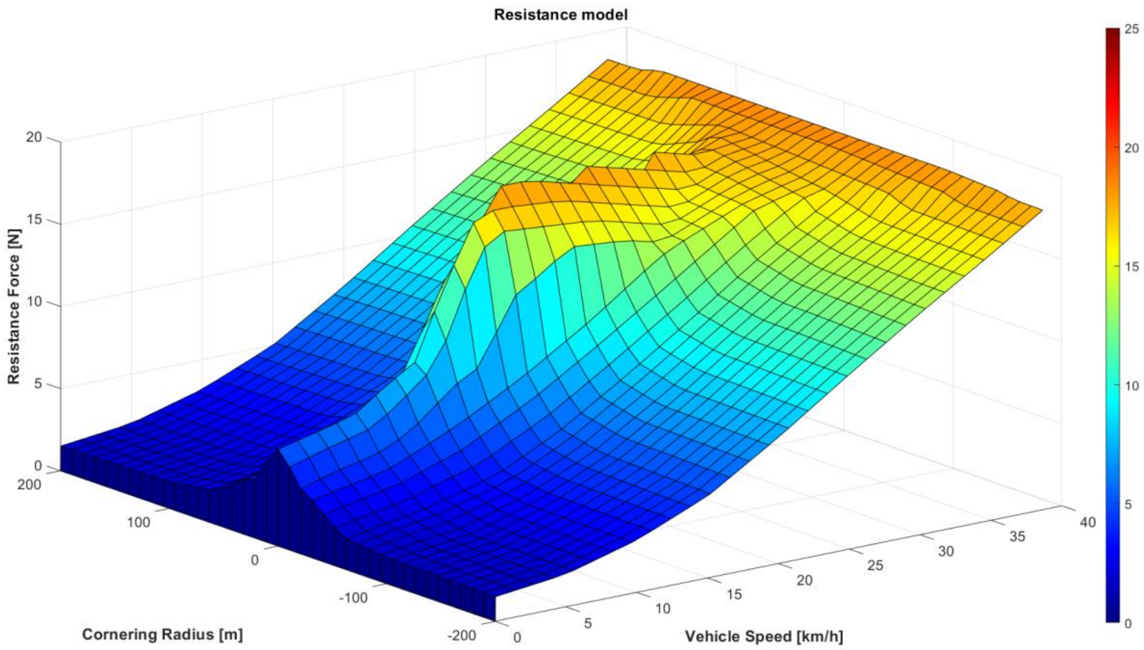

Figure 5: Vehicle dependent extended resistance force model

5. Discussion

The vehicle model described in Figure 2 was set up based on the presented measurements and methods. The proposed methodology is particularly beneficial in creating the resistance force model as every factor and cross impacts of vehicle components are taken into consideration. The method is suitable for avoiding inaccuracies coming from unknown effect of special vehicle characteristics. The presented measurements and evaluations are resource intensive methods and can only be used on test-ready vehicles. Measurements also need to be repeated after any modification on the vehicle, which limits the model applicability. The model can be further developed by including the effect of external factors, such as wind. The designed vehicle model was validated by comparing the measured and calculated energy consumption of the vehicle on a given track. The comparison was made based on logged torque reference of 1 SEM lap back from 2019, this reference served as input for the model. Total energy consumption of 30,421 J was calculated by the vehicle model-based simulation, while the official physical measurement was 30,875 J and the difference is negligible (1.4 %). Initial driving strategy optimization based on the presented vehicle model was made using evolutionary algorithms. MATLAB optimization toolbox was used to specify the algorithm properties. The best human driven SEM lap was compared to the best individual from the evolutionary algorithm. Due to the optimized torque reference, the results showed 7.1 % energy savings on 1 SEM race lap.

6. Conclusion

Novel grey-box model for an energy efficient lightweight vehicle was set up based on systematic measurements. The complete powertrain model was defined by test bench measurements, this model combines the characteristics of the permanent magnet synchronous motor (PMSM), controller, and transmission. The designed extended resistance force model handles the effect of cornering, due to the evaluation of the presented field tests. The generated vehicle dependent model clearly describes all arising resistance forces. Simulation results have proved that the created vehicle model has an appropriate accuracy. Therefore, it is suitable for further investigation of driving strategy optimization. Optimization attempts have resulted in 7.1 % energy savings on 1 Shell Eco-marathon race lap compared to the best human driven lap. Our future research goal is to refine this driving strategy optimization and examine other optimization methods to achieve further energy savings. In the future, optimized driving strategies can be directly implemented in autonomous vehicles to maximize the achievable energy savings. The development of energy efficient driving strategies will be essential in the future for reducing the global CO_2 emission.

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