Article

Optimization of Powertrain in EV

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Abstract: The method for preliminary powertrain design is presented in the paper. Performance of the EV is realized by motor torque–speed curve and gear ratio optimization. The typical two-zone mechanical characteristic of a PMSM traction motor is included in the optimization program. The longitudinal vehicle model is considered in the paper. Some examples try to show the calculation possibilities in application to existing vehicles: Tesla Model S and Mini Cooper SE.

Keywords: electric vehicle; electromechanical systems; optimization; multi-objective optimization; field weakening; traction motors; kinematics; motor torque; gear

1. Introduction

The conversion of electrical energy into mechanical is very important for the drive in an Electric Vehicle (EV) and optimization of the car performance is discussed in the article. The path from battery to a traction force F_T on the car wheels is called powertrain [1,2].

The presented optimization problem can be used to design preliminary powertrain in a EV. The torque–speed curve (mechanical characteristics) [3] of PMSM (Permanent Magnet Synchronous Motor) is introduced. This type of motor is the most popular in car manufacturers (Toyota, Nissan, BMW, Renault), but Tesla induction motor characteristics are also considered. The EV mathematical model is presented more precisely than in [4]. Two design examples are included in the paper: gear ratio optimization in Tesla Model S, traction motor, and gear ratio optimization in the Mini Cooper SE.

The optimization is considered as a Nonlinear Programming Problem because the objective function (performance index) is nonlinear, and a longitudinal model of motion is also nonlinear. The value of the objective function is calculated after car race simulation. Hence, the objective function is not explicit and the Simplex Method (Nelder–Mead Method or Downhill Simplex Method) [5] is very useful because derivatives of the objective function are unknown. In the Matlab environment, `fminsearch` is a Simplex Method without constraints.

The method of the powertrain optimization shows Figure 1.
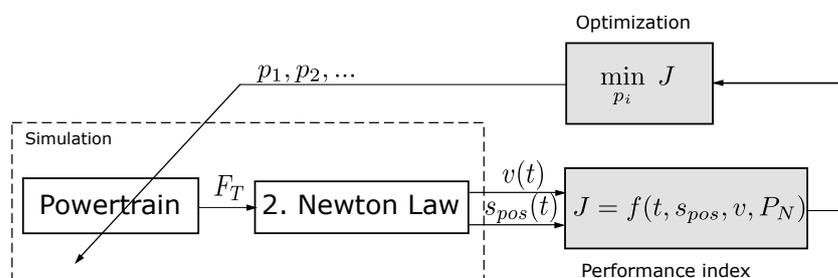
Figure 1. Method of powertrain optimization.

The powertrain parameters that are optimized are p_i, performance index $\mathcal{J}$ can be function of time t, position s_{pos}, speed v or power of the traction motor P_N. The traction force F_T on wheels is the output of the powertrain.

The powertrain optimization is often considered in publications, and there are some examples for EV and Hybrid Electric Vehicle (HEVs). The three ratios of planetary gear in HEV are presented in the paper [6], the optimization objectives include the 0–100 kmh acceleration time, CO emissions, HC compound emissions and NOx emissions under NEDC (New European Driving Cycle) conditions. However, the traction motor is not considered and the obtained results for one objective function are shown, but the optimization method is unknown. The more precise optimization of planetary gear ratios is presented in [7], where Particle Swarm Optimization is used.

The powertrain optimizations for PMSM and induction motors in the electric bus are shown in [8].

The optimization problem where the goal is to minimize the cumulative fuel consumption (for HEV) is considered in the article [9].

Parameters optimization of two-speed powertrain of electric vehicle based on genetic algorithm (GA) is considered in [10]. The different GA for a gearbox optimization (internal combustion engines) is used in the paper [11].

The parameter optimization for the CVT (continuously variable transmission) in 4-wheel drive HEV is considered in [12], where evolutionary based non-dominated sorting genetic algorithms-II (NSGA-II) is used.

The motor (wound rotor synchronous motor and PMSM) efficiency and battery optimization are considered in [13].

This paper shows another objective function (performance indexes) in optimization than previously cited and the deterministic minimization method (Nelder–Mead Method) instead of stochastic optimization. Additionally, three energy storages are included in the vehicle motion mathematical model, not one as in most publications, so the results of the optimization are more real. Some of the presented examples are also multi-objective optimization.

The paper presents: PMSM characteristics, EV model, the Nelder–Mead optimization method, two examples of powertrain optimization (Tesla S Model and Mini Cooper SE) for assumed performance indexes. The EV acceleration to 100 kmh, 1/4 mile and top speed are the indexes considered in the article.

2. PMSM Traction Motors

The work [14] (in 1977) discusses, for the first time, the three-zone angular velocity control of induction motors, which was generalised for other drives [1–3]. Figure 2 shows general characteristics $M = f(\omega)$, $P = f(\omega)$ and flux linkage $\psi = f(\omega)$ for PMSM traction motors.
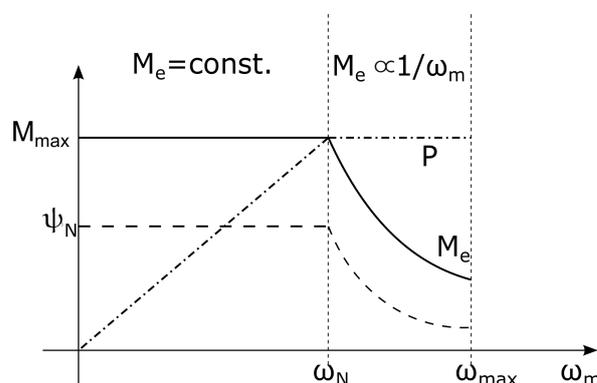
Figure 2. Theoretical two-zone angle velocity control of PMSM.

The control zones shown in Figure 2 represent different types of electric motor operation:

Zone 1: means working for constant torque $M_e = const$ and then the active power transferred to the working machine increases linearly as the angular speed increases ($P_m = M_e \omega_m$). This zone means also working with limited current and constant flux value in the air gap.

Zone 2: means operating at constant active motor power $P_m = P_N = M_e \omega_m$, where the motor's electromagnetic torque changes inversely proportionally to the motor's angular velocity ($M_e \propto \frac{1}{\omega_m}$). In this zone, the supply voltage equals the rated voltage U_N and is the voltage limit. At the same time, the current in the stator winding is rated, and the flux in the air gap is reduced.

The curve from Figure 2 will be used in EV model, which will be optimized.

3. Longitudinal EV Model

The mathematical model for simulation of a EV is described more precisely than in [4].

3.1. Forces

The forces (road loads and traction force) acting on the EV are shown in Figure 3 e.g., [4,15,16].
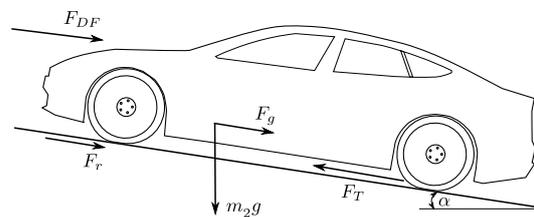
Figure 3. Forces acting on a EV.

Tractive force F_T is function of motor speed ω_m and is described by:

$$F_T = (M_e(\omega_m) - \triangle M)\frac{2i}{d_w} \tag{1}$$

where i is gear ratio, d_w is wheel diameter, and M_e is motor torque.

Total rolling resistance F_r is the sum of the resistances from all wheels [15] ($\cos \alpha$ is neglected because, for a 10% road grade, it is $\cos(\frac{0.1\pi}{4}) = 0.9969$):

$$F_r = f_r m_2 g, \quad f_r = f_0\left(1 + \frac{v}{161}\right) \tag{2}$$

where v is EV speed in kmh and the rolling coefficient is $f_0 = 0.01 \div 0.02$ for a concrete surface.

Aerodynamic drag force:

$$F_{DF} = \frac{1}{2}\varrho \, C_d A(v - v_w)^2 \tag{3}$$

where $\rho = 1.225 \text{ kg/m}^3$ is air density, A is the cross sectional area (frontal area) of EV, C_d is drag coefficient, and the speed of wind is v_w.

Grade resistance is described as:

$$F_g = m_2 g \sin(\alpha) \tag{4}$$

Newton's second law for longitudinal motion of EV is in the following form:

$$m \underbrace{\frac{dv(t)}{dt}}_{a(t)} = F_T(t) - \underbrace{(F_{DF}(t) + F_r(t) + F_g(t))}_{F'(t)} \tag{5}$$

The F_{DF} and F_T are nonlinear functions, so the ordinary differential Equation (5) is nonlinear too. Thus, the numerical solution of this equation will be used in the optimization of the powertrain in EV.

3.2. Torques, Mass, and Moments of Inertia

The forces from Figure 3 and torques in the powertrain are shown in Figure 4.
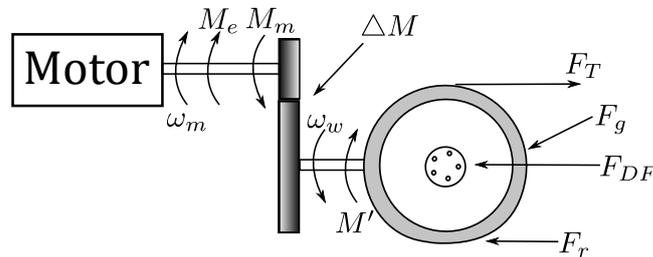
Figure 4. Simplified powertrain.

The conversion of the road loads F' to torques on the motor shaft by gear is described as:

$$M_m = \triangle M + \frac{M'}{i}, \quad M' = \frac{F'd_w}{2} \tag{6}$$

where Coulomb friction can be calculated as load torque [17]:

$$\triangle M = M_{\max}(1 - \eta) \cdot sign(\omega_m) \tag{7}$$

Three kinetic energy storages are found in every EV. The first two storages are: rotor moment of inertia J_1 and a vehicle mass (m_2); the equivalent mass or moment of inertia are:

$$m_1 = J_1 \frac{4i^2}{d_w^2}, \quad J_2 = m_2 \frac{d_w^2}{4i^2} \tag{8}$$

the values m_1, J_1 are much smaller than m_2, J_2.

The next energy storages are the remaining rotating elements: wheels (rims and tires), brake discs, shafts, etc. Considering any rotating mass m_i of radius r_i, it is possible to determine its moment of inertia or to specify an equivalent mass (for horizontal motion) of the same kinetic energy:

$$J_i = m_i r_i \tag{9}$$

J_i is each rotating element in power transmission. Hence, the principle of the energy conservation results in the formula:

$$\frac{m_{3i}v^2}{2} = J_i \frac{\omega^2}{2} \tag{10}$$

where m_{3i} is the equivalent of mass calculated on the vehicle body. If v is car speed and radius of wheels is $r_w = d_w/2$, then Equation (10) leads to:

$$\frac{m_{3i}\omega^2 r_w^2}{2} = \frac{m_i r_i^2 \omega^2}{2} \implies m_{3i} = m_i \frac{r_i^2}{r_w^2} \tag{11}$$

For example, four wheels, each weighing 20 kg, should be added to the vehicle's weight as 80 kg, while four brake discs, each weighing 3 kg and their diameter being half the size of the wheel, should be reduced four times, i.e., 3 kg should be added to the vehicle body.

Thus, small diameter and small mass rotating elements can be omitted from the mathematical model. In summary, the total moment of inertia that is reduced to the motor shaft and the total mass reduced to the EV body are:

$$J = J_1 + J_2 + \frac{\sum_i J_i}{i^2}, \quad m = m_1 + m_2 + \sum_i m_{3i} \tag{12}$$

Hence, the Newton's second law is in the following form:

$$J\frac{d\omega_m(t)}{dt} = M_e(t) - M_m(t) \tag{13}$$

Equations (5) and (13) describe the same electromechanical system, but in different reference frames.

3.3. Model

Equations (5) and (13) lead to the block diagram in Figures 5 and 6. The block Motor + Control is the torque–speed curve of a traction motor drive system that is presented for PMSM in Figure 2. The Coulomb friction $\triangle M$ is included in both models. In the block diagrams, three energy storages are considered that are given by Formula (12). The diameter of the wheels is d_w, which changes rotational motion to longitudinal, and is found in every scheme because the torque M' also depends on d_w (6).
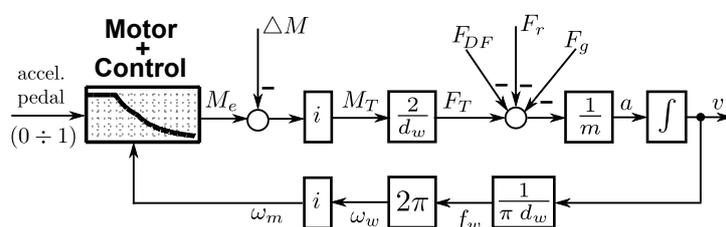
Figure 5. Powertrain model ver. 1.
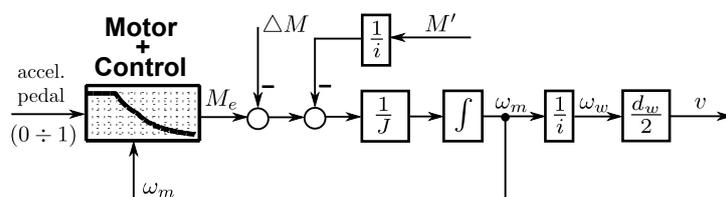
Figure 6. Powertrain model ver. 2.

The proposed model is not complicated like in, e.g., a Powertrain Blockset toolbox, which is the Matlab-Simulink environment, but should be sufficient for the preliminary design of the drive.

4. Optimization of Powertrain

The Nelder–Mead method [5] is used to optimize the gear ratio and the torque–speed motor curve in the powertrain of EV. The names Simplex method or amoeba method are used here.

A simplex is considered to be a convex figure in n-dimensional space that has $n + 1$ vertices. This means that, for $n = 1$, it is a segment, for $n = 2$ a triangle, and, for $n = 3$, a tetrahedron. To determine the minimum of the objective function, the following operations are performed on the simplex: sort, reflect extend, contract, shrink. Hence, for two dimensions, the search for the minimum of a function is similar to a moving amoeba.

Optimization of powertrain is realized by (as in Figure 1):

1. Initial conditions: gear ratio i and torque–speed curve (block Motor + Control in Figure 5).
2. EV model simulation (Figure 5).
3. Calculating of performance index (objective function) $\mathcal{J}$.
4. Minimization, which leads to new values of the gear ratio i and the torque–speed curve.
5. Checking the stop condition: max iterations and errors, which leads to points 2 or 6.
6. Stop.

The next two sections present a lot of powertrain optimization examples.

5. Gear Ratio Optimization in Tesla Model S P85

The Tesla Model S powertrain is one of the best known, and has been chosen as an example of the gear ratio selection for different tasks (performance).

Figure 7 presents torque–speed and power–speed curves of the traction motor in the considered EV (red color).
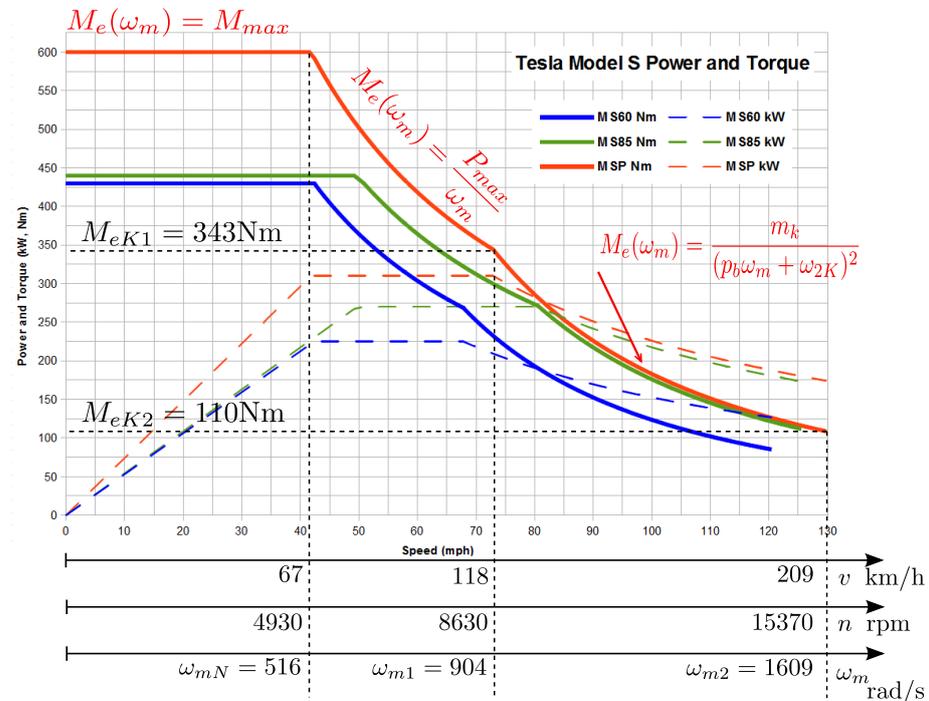
Figure 7. torque–speed and power-speed curves of the EV.

Figure 7 shows 3 modes (zones) of operation for the induction motor:

- Mode 1: as in Figure 2,
- Mode 2: as in Figure 2,
- Mode 3: constant power × rotor angular velocity region, slip frequency is constant and equals ω_{2K} (critical value, pull-out frequency). This region exists only in the induction motors and PMSM has only two modes.

The parameters of the previous model for Tesla Model S P85 are included from [4], and they are assumed as:

- $m_2 \approx 2100 + 100 = 2200$ kg,
- $J_1 \approx 0.06$ kgm^2,
- $C_d = 0.24$, frontal area of the vehicle $A = 2.4$ m^2,
- $i = 9.73, \eta \approx 0,97$ (assumed in [18]), which lead to $\triangle M = 18sign(\omega_m)$.
- Equations (8) and (11) lead to: $m_1 = 46$ kg, $m_3 = 120$ kg.
- $d_w = 0.703$ m.

Tesla Model S P85 (2012) [19]. This vehicle has the following performance:

- 0–60 mph (0–96.6 km/h): 4.6 s,
- 1/4-mile (402.5 m): 13.3 s and speed: 104 mph (167.5 km/h),
- top speed: 134 mph (215.7 km/h), which leads to $v_{\max} = 59.9$ m/s.

Simulation results for original gear ratio are presented in Figure 8, where t_{100} is acceleration time to 100 kmh, $t_{1/4}$ is time for 1/4 mile. The obtained results are similar to the vehicle catalog data. Simulations are realized as numerical integration (Euler method, with step 0.01 s) nonlinear differential equation in Figure 5 where "Motor + Control" is the torque–speed curve in Figure 7.
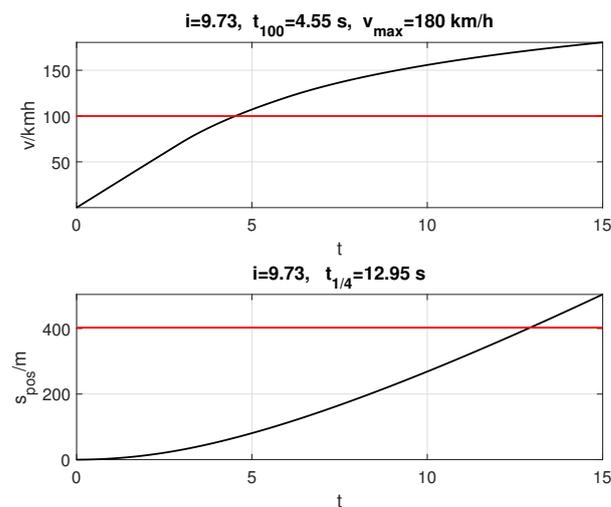
Figure 8. Performance of EV for nominal gear ratio.

Now, the car performances can be improved, so the optimization problem is considered in the following form:

$$\min_i \mathcal{J} \tag{14}$$

where $\mathcal{J}$ is objective function (performance index) and $\mathcal{J}$ can be equal t_{100}, $t_{1/4}$ or v_{max}. The result of optimization is gear ratio i. The Simplex method (Figure 1 and description in Section 4) is used for minimization. The results of optimization for performance index $J = t_{100}$ are shown in Figure 9.
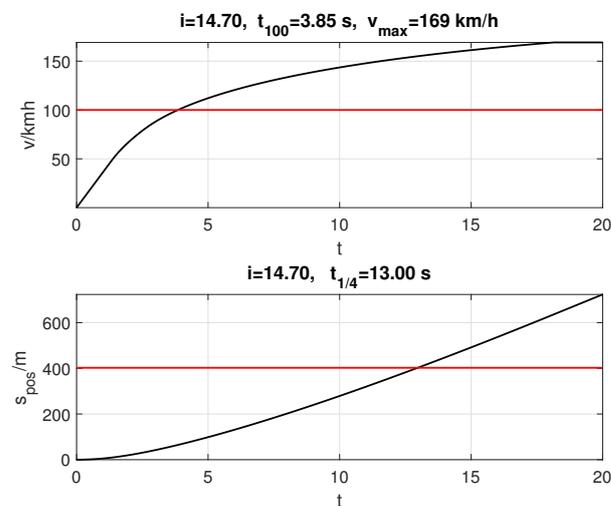
Figure 9. Optimized gear ratio i of EV for $J = t_{100}$.

Obtained results are displayed in figures with simulation. The next optimization problem can be minimization of the time $t_{1/4}$, then $i = 11.45$ and race time is $t_{1/4} = 12.85$ s, so the simulation results are similar to what is presented in Figure 9, and they are omitted.

Ref. [19] reads: "With taller gearing, a P85 Model S might reach 200 mph. Clearly, this is the aerodynamic electric car that merits intense scrutiny by the world's carmakers". Hence, if $\mathcal{J} = -v_{max}$ (maximization speed can be written as minimization, thus sign '−') and simulation time is longer, e.g., 100 s, then optimization can find the i. Figure 10 presents obtained results, so, for gear ratio 3.73, maximum speed is near 200 mph.

Summing up the main points, an obvious qualitative conclusion can be given, which is supported by quantitative data: different gear ratios should be used for different tasks. Thus, the optimization of torque–speed curve and gear ratio will be presented in the next section.
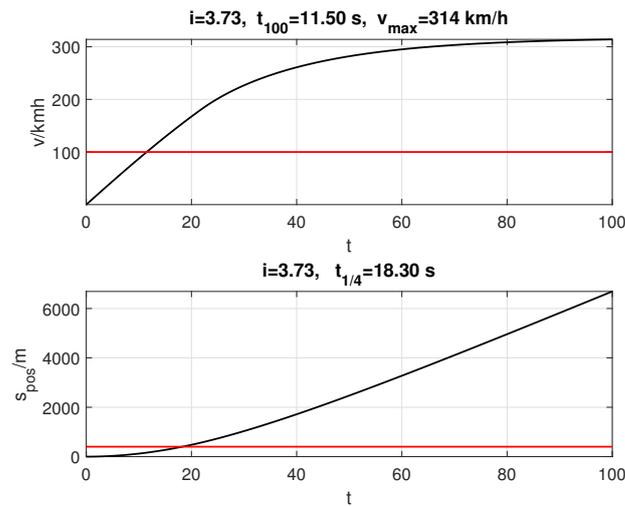
Figure 10. Optimized gear ratio i of EV for $J = -v_{max}$.

6. Powertrain Optimization for Mini Cooper SE

A modern car like Mini Cooper SE was chosen as an example of EV. The maximum torque of the traction motor and mechanical gear will be optimized. The characteristics are adopted in a two-zone form as for PMSM motors, and the ratio of ranges is 1:2, so in Figure 2 $\omega_N = 1/3\omega_{max}$:

- $0 \div 1/3\omega_{max}$ constant torque region: $M_e = M_{max}$,
- $1/3\omega_{max} \div \omega_{max}$ constant power region: $M_e = \frac{P_N}{\omega_m}$.

The basic parameters of the considered car from the manufacturer's website or https://www.carfolio.com are:

- car and driver mass $m \approx 1365 + 100$ kg,
- drag coefficient $C_d = 0,3$, frontal area $A = 2.1$ m^2,
- gear ratio $i = 8.96$,
- tires: P205/45R17, which leads to wheel diameter $d_w = (17 \times 25.4 + 2 \times 205 \times 0.45)/1000 = 0.616$ m, thus the circumference of the wheel is 1.935 m,
- maximum speed $v_{max} = 150$ kmh, acceleration 0–100 km/h equals 7.3 s.
- PMSM 135 kW (from 7000 obr/min), maximum torque $M_{max} = 270$ Nm (0–1000 obr/min). Knowing the maximum speed of the vehicle, the transmission and the wheel circumference can calculate the maximum speed of the electric motor:

$$\omega_{max} = \frac{v_{max}}{3.6}\frac{1}{\pi d_w}2\pi i = 1212 \text{ rad/s} \quad \rightarrow n_{max} = 11.580 \text{ rpm}$$

The original motor will be neglected in the remainder of this paper, but a new torque–speed curve of the motor and gear ratio will be calculated by optimization for the performance requirements that will be written in the objective function $\mathcal{J}$.

The design takes into account the influence of PMSM motor power on the moment of inertia and vehicle mass.

In the optimization, changes are assumed in the traction motor moment of inertia J_1, considering the factor: $\frac{0.05 \text{ kgm}^2}{100 \text{ kW}}$. This value for PMSM is higher than for the squirrel cage motor in [4] and can be recalculated to car body mass m_1 by Formula (8).

The second mass of m_2 will also vary with the traction motor power (mass of motor, power electronics and electrical equipment), and it includes the 135 kW of Cooper SE motor (the factor is $\frac{0.5 \text{ kg}}{1 \text{ kW}}$), which leads to: $m2 = m + (P_N - 135,000)/1000 \times 0.5$, where m is car and driver mass.

The next mass $m_3 = \sum_i m_{3i}$ is constant (11) and is assumed as 80 kg. Hence, in the EV simulation, the total mass described by the Formula (12) is used.

The performance index for the acceleration time can be described as:

$$\mathcal{J} = (t_{100} - t_{100opt})^2 \tag{15}$$

where t_{100opt} is desired time to 100 kmh. An example of optimization ($t_{100opt} = 4$ s) is in Figure 11, where the initial conditions were $M_{max} = 370$ Nm and $i = 13$.
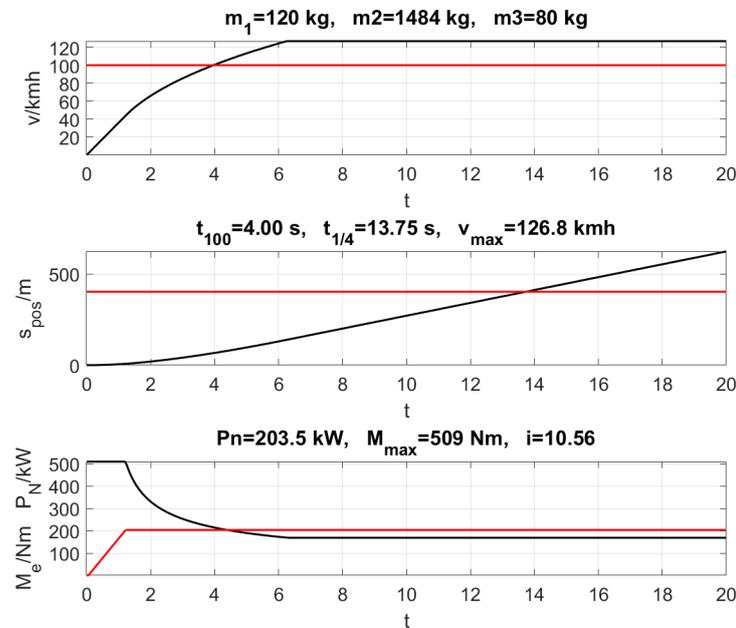
Figure 11. Optimized powertrain for 4 s acceleration to 100 kmh.

For different initial conditions, different results are obtained and the motor power increases up to 271 kW, so it is necessary to modify the objective function (15), e.g., the motor power is taken into account, and this leads to (multi-objective optimization):

$$\mathcal{J} = (t_{100} - t_{100opt})^2 + \alpha P_N \tag{16}$$

where α is the weighting factor which brings P_N down to a similar numerical level. For example, $\alpha = 2.5 \times 10^{-5}$, and optimization results are shown in Figure 12 (initial conditions do not matter for the optimization result).

Modification of the index $\mathcal{J}$ by power P_N causes the assumed time not to be reached, so you can take a smaller value t_{100opt} or reduce α. For $t_{100opt} = 3.35$ s, the time $t_{100} = 4$ s is reached, and powertrain is characterized by: $P_N = 199$ kW, $M_{max} = 497$ Nm and $i = 12.67$. Hence, it is a better result than optimization with performance index (15) with different initial conditions. Moreover, αP_N has the role as a penalty function, so we can talk about optimization with constraints here.

The last example will be about using a multi-task objective function in the following form:

$$\mathcal{J} = (t_{100} - t_{100opt})^2 + \alpha P_N + \beta(t_{1/4} - t_{1/4opt})^2 + \gamma(v_{max} - v_{maxopt})^2 \tag{17}$$

where $t_{1/4opt}$ and v_{maxopt} are desired values of the car performance and α, β, γ are the weights of the respective objective function components. Optimization of the drive for dynamic but not sporty EV is shown in Figure 13, where it is assumed: $t_{100opt} = 6$ s, $t_{1/4opt} = 14$ s, $v_{maxopt} = 200$ kmh and weights $\alpha = 2.5 \times 10^{-5}$, $\beta = 0.33$, $\gamma = 0.05$.

The obtained results are similar to the reference values, the motor power is not so high, and the powertrain parameters are similar to cars with internal combustion engines. Thus, performance index (17) can be used for preliminary drive design.

Table 1 collects the results from this chapter, where three performance indexes are considered.
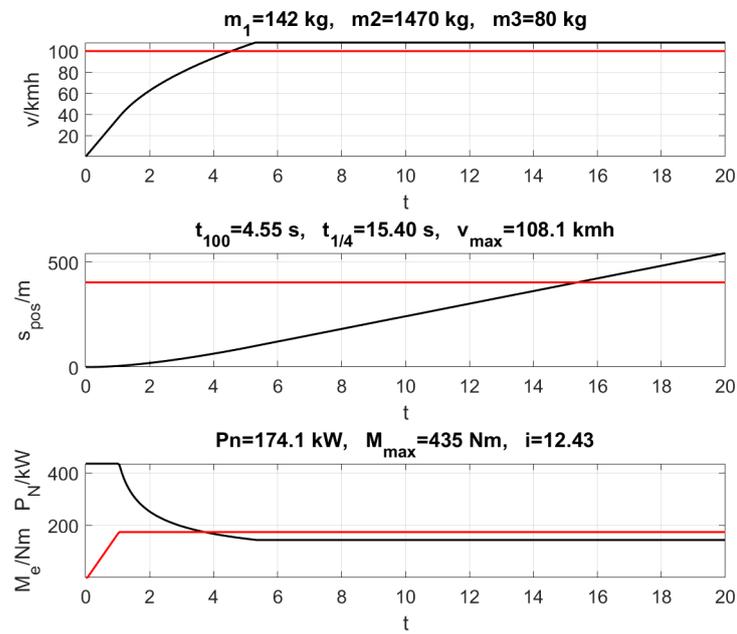
Figure 12. Optimized powertrain for 4 s acceleration to 100 kmh and motor power minimization.
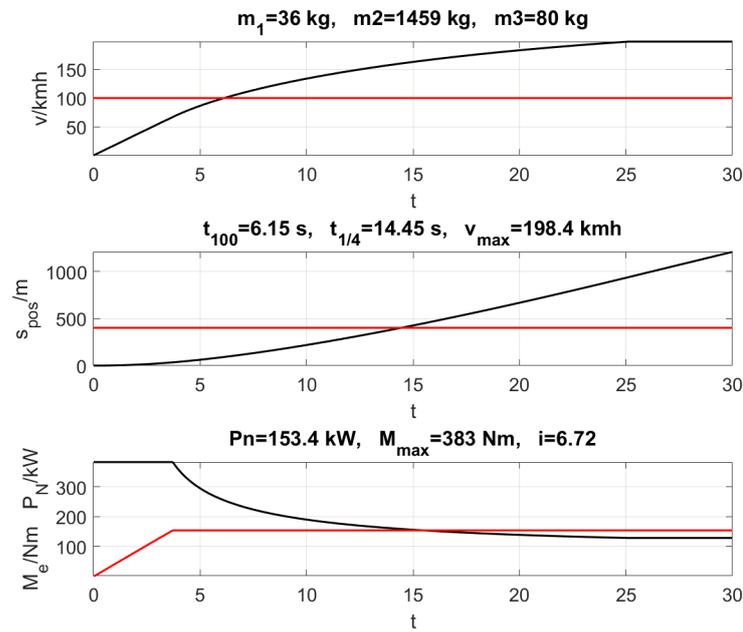
Figure 13. Optimized powertrain.

Table 1. Powertrain optimization for different performance indexes.

$\mathcal{J}$	m_1 [kg]	m_2 [kg]	t_{100} [s]	$t_{1/4}$ [s]	P_N [kW]	M_{max} [Nm]	i
$(t_{100}-4)^2$	120	1484	4.00	17.75	204	509	10.56
$(t_{100}-4)^2 + \alpha P_N$	142	1470	4.55	15.4	174	435	12.43
$(t_{100}-6)^2 + \alpha P_N + \ldots$ $+\beta(t_{1/4}-14)^2 + \gamma(v_{max} - \frac{200}{3.6})^2$	36	1459	6.15	14.45	153	383	6.72

The first performance index is only set to accelerate to 100 kmh in 4 s and, as a result of optimization, this assumption is obtained. In the second case, P_N appears in the performance index, and it leads to a motor power reduction, but the acceleration time is longer $t_1 00 = 4.55$ s. Thus, αP_N is similar to the penalty function—optimization with constraints. If α is higher, the power will be lower. The third case is the most reasonable because it takes into account all vehicle performances while limiting motor power. The last case is multi-objective optimization.

7. Conclusions

The methods for preliminary powertrain design are presented in the paper. In contrast to the often used genetic algorithms in this field, the Nelder–Mead (Simplex) method has been used. This method is much simpler than genetic algorithms and, after the results, it seems sufficient for this stage of EV powertrain design.

Three energy storages (motor moment of inertia; total car mass; wheels and brake discs and halfshaft moments of inertia) are included in the EV mathematical model, which is also rare in another papers. Appropriate formulas are given to convert masses or moments of inertia to the electric motor or the vehicle body side.

The optimization results are presented for Tesla Model S P85 and Mini Cooper SE. In the first car, the motor torque–speed characteristics were maintained, and the optimum gear ratio was found for the various performance targets. For Cooper, the mechanical gearbox and maximum of electromagnetic torque (the shape of the torque–speed characteristics was assumed) were optimized. Moreover, the motor power P_N influences the motor moment of inertia J_1 and the mass of the vehicle m_2. Hence, P_N additionally changes Newton's 2nd law in Figure 1.

Solved nonlinear programming problems look promising and can be extended, e.g., by vehicle range (battery weight will increase) and more precise motor characteristics (as for Tesla), etc. In addition, constraints for the cost function can be introduced as constraints on component cost (motor, batteries), weight. In this optimization problem, the penalty function is most preferred.

The presented solution should be used for preliminary vehicle powertrain design, while e.g., the Powertrain Blockset toolbox (Matlab-Simulink environment) can be used for precise modeling.

Institutional Review Board Statement: Not applicable.

Informed Consent Statement: Not applicable.

Conflicts of Interest: The author declares no conflict of interest.

Abbreviations

The following abbreviations are used in this manuscript:

EV　　　　Electric Vehicle
PMSM　　Permanent Magnet Synchronous Motor

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