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MULTI-OBJECTIVE OPTIMIZATION OF GEAR RATIOS IN TWO-SPEED DUAL CLUTCH TRANSMISSIONS FOR ELECTRIC VEHICLES

Yiyi Liang[a], Haiping Du[a*]

[a]*School of Electrical, Computer and Telecommunications Engineering, University of Wollongong, Australia*

Abstract

The rational matching and optimized design of the gear ratios for the transmission system of an electric vehicle (EV) are of great importance for improving economic and dynamic performances. This paper sets a pure electric vehicle (PEV) as the research object. First, the four common driving cycles considering the urban and suburban areas are selected and analysed which are applied for designing the gear ratios. Second, the parameter matching of the basic indicators of the EV performance and the selection of gear ratios are explored according to the analysis of the four selected driving cycles. Furthermore, gear ratios are set as the variables and the ant colony optimization (ACO) algorithm is applied to optimize the gear ratios by setting the sum of the power demand of the selected common driving cycles, the sum of the average motor efficiency of the chosen driving cycles, and the acceleration time as the objective function in order to optimize the vehicle performances. A two speed dual clutch EV model is constructed in MATLAB/Simulink for verification of the results. The simulation results demonstrate the effectiveness of the optimisation in comparison with the previous gear ratios, where both economic and dynamic performance improvements are evident.

Keywords: Gear ratio optimization, Ant colony optimization, two speed electric vehicle

1. Introduction

A pure electric vehicle (PEV) has attracted lots of attention due to its advantages of low carbon emissions and using a renewable energy source, electricity. By virtue of these advantages, PEVs solve the current environmental issues caused by conventional vehicles with internal combustion engines (ICEVs), which are regarded as the most suitable alternatives to ICEVs. In the current commercial market, most PEVs feature a single-speed transmission and fixed ratio reducer due to the characteristics of electric motors and the considerations of manufacturing complexity and cost. A one-speed transmission, however, is unable to handle a wide range of requirements and vehicle performances. Equipping a two-speed transmission can greatly enhance both the economical and dynamic performances of PEVs.Therefore, it is paramount to investigate the parameters of a PEV, in this paper, the gear ratios inside the powertrain of a PEV will be investigated explicitly.

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Gear ratio is an important parameter in EV powertrains, affecting both the vehicles' economic and dynamic performances. Larger gear ratios are generally correlated with take-off and climbing abilities, which facilitate greater initial torque, while smaller gear ratios are related to the maximum speed (Wang et al.,2013). Therefore, gear ratio optimization is a multi-objective problem (Kwon et al.,2019). According to the current literature, the two main optimization methods for gear ratio are genetic algorithm (GA) and particle swarm optimization (PSO) respectively. While both algorithms are used for global optimization problems, their objective functions vary based on specific requirements. In the case of GA, Walker et al. (2013) proposed a gear ratio optimization method using GA to maximize motor efficiency and maximum mileage as the objective function. Tang et al. (2014) also applied GA in the optimisation of gear ratios by taking the minimization of NEDC driving cycle energy consumption into the purpose and conducted a comparative study of the performance from previous gear ratios and the optimized gear ratios. In terms of PSO, Gu et al. (2012) suggested using PSO in implementing the selection of gear ratios. PSO has the advantages of parallel computation, rapid searching ability and being robust for non-linear problems, which makes it one of the useful methods in the optimisation problems of vehicles. Tan et al. (2018) applied PSO in the design of gear ratios considering energy consumption and dynamic performance via acceleration as the objective function. Based on the literature, it has been proven that algorithms like GA and PSO have been successfully applied to gear ratio optimization in numerous examples, validating it as an effective method that requires less information and computation while achieving expected results.

Dual clutch transmission (DCT) is an ideal transmission system for two speed PEVs. DCT deploys two clutches, the odd clutch, and the even clutch work alternately to provide excellent shifting quality. It can achieve a satisfactory shifting quality because the alternation between two clutches realizes minimal power interruption in the shifting process. DCT demonstrates better fuel economy and smoother shifting with high accuracy, which makes it suitable for EVs. DCT also has the advantage of improving driving comfort with fewer interruptions or shift shocks. As a result, it has attracted researchers' attention for research that can be applied by automobile manufacturers around the world (Zhu et al.,2013, Walker et al.,2011).

The literature review indicates that it is important to examine the design and optimization of gear ratios as they affect operational performance. In this paper, this study aims to develop and enhance gear ratios for a two-speed DCT in PEVs by considering economic and dynamic performances, addressing power demand, motor efficiency and acceleration as objectives. The selection of gear ratios is designed based on the analysis of the four common driving cycles. The optimization is carried out using ant colony optimization (ACO) to obtain the optimized solution. An electric vehicle model with two speed DCT was constructed, and simulation analysis was performed using MATLAB and Simulink. Simulated results indicate that the optimized gear ratios are valid and meet both power and economic performance requirements.

2. Analysis of Common Driving Cycles

An EV can encounter a variety of different complex driving conditions, such as congested traffic which often occurs in urban cycles, and comfortable high-speed driving which often occurs in highway or suburban cycles. Consequently, a vehicle's performance can be affected by those varying road conditions and driving modes, for example, the acceleration, climbing, and braking ability are affected by real-time road conditions. Nonetheless, it is difficult to predict and obtain real-time driving conditions in the time domain, thus, researchers combine and generate some representative driving cycles through the statistical approach. A statistical approach is formulated by testing, comparing, and analyzing the driving data by selecting the representative vehicle driving cycles. In this study, the commonly used driving cycles were selected to analyze and obtain their characteristic parameters. The driving cycles studied here are the New European Driving Cycle (NEDC), Urban Dynamometer Driving Schedule (UDDS), Highway Fuel Economy Test (HWFET), and US06 drive cycle (J. Xu et al.,2022). The background of each driving cycle is presented below:

HWFET describes highway driving conditions, which are also conducted by the EPA to determine fuel consumption on highways, as demonstrated in Fig.1.1.a.

The UDDS driving cycle as shown in Fig.1.1.b is obtained in the United States which is obtained from the dynamometer test on fuel economy conducted by the United States Environmental Protection Agency (EPA). It describes the city's driving conditions in light-duty vehicles.

The NEDC drive cycle is a classic driving cycle that represents the typical usage of an automobile in Europe and has been utilized in scientific research widely. This is combined with four repeated urban driving cycles and one extra-urban driving cycle, as demonstrated in Fig. 1.1.c.

Moreover, US06 is used as an additional driving cycle to supply the studies of driving cycles. It is a current profile for an electric vehicle battery pack in realistic driving conditions. The entire cycle of US06 is indicated in Fig.1.1.d.

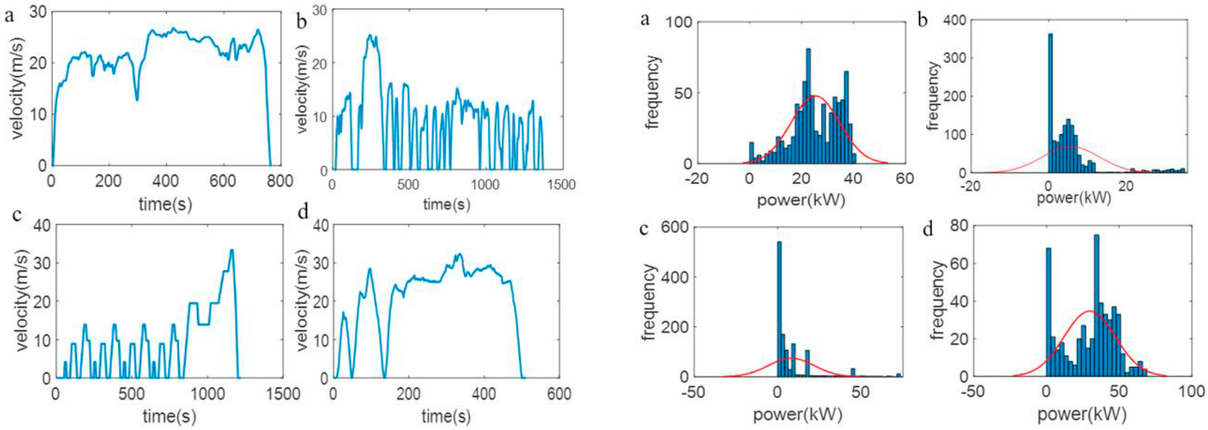

Fig.1. Driving cycles (1) and Power vs Frequency (2): a. HWFET b. UDDS c. NEDC d.US06

Based on the analysis of those selected driving cycles, the maximum velocity for each cycle is:

Table 1. Maximum and Average Velocity for Each Driving Cycle

Driving Cycle	Maximum Velocity (m/s)	Average Velocity (m/s)
NEDC	33.33	8.96
UDDS	25.2	8.7012
HWFET	26.7720	21.544
US06	32.3075	21.1982

In order to better combine the power demand of pure electric vehicles and the driving conditions, the power for each driving cycle is calculated and distributed into different segments. The formula of power is defined as:

$$P = mgf + \frac{C_d A_a v^2}{21.15} \cdot \frac{v}{3600 n_t} \quad (1)$$

Where m is the vehicle mass, g is the gravitational force, f is the rolling friction coefficient, C_d is the drag coefficient, A_a is the wind area and n_t is the transmission efficiency. Thus, the power demand distribution for each cycle is illustrated as histograms with normal distribution fit in Fig.1.2. The mean values of the power demand for the four cycles are 5.6771 for UDDS, 8.1257 for NEDC, 29.6873 for US06, 25.2615 for HWFET. From the result, it is obvious that the power demand for operating in the highway scenario is higher than the vehicle running in the urban scenario. The analysis of each drive cycle will be useful for the determination of the basic indicators of vehicle performance and the range of gear ratios, as those driving cycles cover both urban and suburban areas, which will be discussed in Section 3.

3. Selection of Gear Ratios

The selection of gear ratios is an integral part of designing a two-speed powertrain system, as gear ratios can be directly associated with an EV's economical and dynamic performance. In this study, gear ratio constraints were derived from the characteristic parameters and performance requirements obtained from commonly used driving cycles. A major goal of optimization of gear ratios is to minimize the amount of energy consumed.

3.1. Gear Ratio Constraints for The First Gear

The gear ratio constraint for the first gear is based on the vehicle's climbing capability. The first gear ratio should have a minimum value that meets the maximum road grade that can be ascended by the vehicle. The following constraints are subject to when determining the first gear ratio:

$$i_1 \geq \frac{mg\left(f\cos(\alpha)+\sin(\alpha)+C_d*A_a*\frac{v_p^2}{21.15}\right)r}{T_{motor}*\,\eta_T*i_0} \quad (2)$$

Where T_{motor} is the motor torque, nt is the transmission efficiency and v_p is the climbing velocity. The main parameters of the vehicle are indicated in Table 2.

Table 2. Vehicle Parameter

Parameter	Value
Vehicle mass m (kg)	1300
Wind area A[m^2]	4
Drag coefficient C_d	0.65
Final drive ratio i_0	6.15
Rolling resistance coefficient f	0.02
Transmission Efficiency η_T	0.85 for the overall transmission system
Dynamic Tire radius[m]	0.33
Maximum ascendable road grade α	30 degrees

In this study, the motor torque is bounded by the power demand of each driving cycle, and the power demand is selected from the mean values of the normal distributions indicated in Fig.1.2 as discussed in the previous section. The relationship between motor power and motor torque is formulated as:

$$P_{motor} = \frac{T_m n_e}{9550}\eta \quad (3)$$

Where T_m represents the motor torque, n_e represents the motor speed and η is the efficiency of the motor, and the relationship between motor speed and the vehicle speed can be described as:

$$n_e = \frac{30 i_0 v}{\pi r} \quad (4)$$

Where i_0 is the main reducer ratio, v is the vehicle speed and r is the tire radius.

As a consequence, the motor torque obtained from each driving cycle can be calculated as: 72.29 N/m for NEDC, 52.01 N/m for UDDS, 93.47 N/m for HWFET, and 111.64 N/m for US06. From the analysis above, the basic indicators of vehicle performance can be determined. Consequently, the maximum motor torque for the motor is selected as 130 N/m and the maximum velocity is chosen to be 120 km/h based on the maximum velocity of the selected driving cycles to accommodate the operational requirement. Furthermore, the climbing velocity is determined from the average velocity, which is selected to be 72 km/h.

The upper bound is regulated by the driving force that is transmitted to the ground through the wheels which are limited by ground adhesion. The formula of the driving force is expressed as:

$$F_N = \frac{mg\left(b\cos(\alpha) - h_g\sin(\alpha)\right)}{L} \quad (5)$$

Therefore, the upper bound of gear 1 is expressed as:

$$i_1 \leq \frac{F_N \mu r}{T_m i_0 \eta_t} \quad (6)$$

In this case, L is the wheelbase, chosen to be 2 meters, b is the distance from the center of the mass to the rear axle(1m) and h_g is the height of the car from the center of the mass (0.5m), μ is the ground adhesion coefficient (0.9).

3.2. Gear Ratio Constraints for The Second Gear

To ensure the vehicle functions well, the car should work smoothly in second gear, as first gear is often used for starting and climbing hills. Therefore, when the car is travelling at high speed, the second gear should be working well to ensure that the drive motor is working in the high-efficiency range to reduce energy loss and increase mileage. It is for these reasons that the upper and lower limits for the second gear are designed to be associated with the maximum speed of the car and the maximum speed of the drive motor. The upper bound of the second gear is demonstrated in Eq. 7:

$$i_{2\_} \leq \frac{3.6\pi n_{maximum}}{i_0 v_{maximum}} \tag{7}$$

The lower bound is bounded by the upper bound of the second gear, indicated in Eq.8:

$$i_2 \geq \frac{i_{2upper}}{3.4} \tag{8}$$

4. Optimization of Gear Ratios Using Ant Colony Algorithm

4.1. Background Of Ant Colony Algorithm

Small animals in nature, such as ants, are often neglected by humans. Nevertheless, it is also fascinating and amazing to observe that such small insects as ants are capable of exhibiting smart behaviours that can be employed in human advanced technology, for example, artificial intelligence. The ant colony algorithm (ACO) is based on ants' behaviours and is inspired by the foraging of ants. Ants can always know the way to discover the shortest path between the sources of food and nests even without any hint, that's because they deposit pheromones on the ground to mark favourable paths that can be followed by other members of the colony (Dorigo et al.,2006). The pheromones will evaporate over time and the probability of the following ants selecting the path is proportional to the intensity of the pheromones on the path. The more ants passing by, the greater the intensity of the pheromones. Therefore, a positive feedback mechanism is generated, and ants are capable of realizing the shortest paths based on this mechanism (Bonabeau and Theraulaz,2000). The advantages of ACO over GA and PSO are its ability to adapt to changes in real-time, robustness, parallelism which allows searches to be independent of ants, and excellent performance in global search.

4.2 Algorithm of Ant Colony Optimization

The algorithm of ant colony optimization can be expressed as: at the start of the algorithm, assign m number of ants. These m numbers of ants update the pheromone values denoted as τ_{ij} where i and j refer to the edge joining cities, and a solution is constructed during each iteration (Dorigo et al.,2006). The equation is written as:

$$\tau_{ij} \leftarrow (1-\rho)\tau_{ij} + \sum_{k=1}^{m} \Delta\tau_{ij}^{k} \tag{9}$$

Where ρ refers to the evaporation rate, and $\Delta\tau_{ij}^{k}$ is the quantity of the pheromone on the edge i and j and k is the ant.If the ant does not pass by (i, j),the value of $\Delta\tau_{ij}^{k}$ will be zero. Based on this, $\Delta\tau_{ij}^{k}$ can be expressed as:

$$\Delta\tau_{ij}^{k} = \begin{cases} \frac{Q}{L_k} \\ 0 \end{cases} \tag{10}$$

Where Q is a constant and L_k is the length of the tour constructed by k.

Each ant going through the city is conducted through a stochastic mechanism, at time t, the probability of the ant k transferred from city *i* to city *j* is:

$$p_{ij}^{k} = \begin{cases} \frac{\tau_{ij}^{\alpha}}{\sum_{c_{il} \in N(s^p)} \tau_{ij}^{\alpha} \eta_{ij}^{\beta}} \\ 0 \end{cases} \tag{11}$$

Where $N(s^p)$ is feasible and implies the city *l* not visited by ant *k* yet. The heuristic information η_{ij} is proportional to the distances between city *i* and city *j*.

4.3 Implementation of Gear Ratios Using ACO

Both dynamic and economic performance are considered in the objective function. Economic performance is generally related to the operating cost of an EV, so the average power demand of the selected driving cycles as well as the sum of average motor efficiency for the four driving cycles are chosen as the economic objective in the fitness function. In addition, dynamic performance is related to acceleration which is generally used to describe the acceleration performance of vehicles; thus, dynamic performance is assessed using the acceleration time from 0 to 100 km/h on flat road.

The input variables for the ACO are the first gear ratio and the second gear ratio $[i_1, i_2]$.In order to avoid the power interruption, the values between gear 1 and 2 shouldn't be too large. Hence, the division between gear 1 and 2 are set to be bigger than 1.3 and less than 1.7.

The power demand is calculated as:

$$P = \frac{mgfv}{3600} + \frac{mgi_1 i_2 i_0}{3600}v + \frac{C_d A_a v^3}{76140} + \frac{\delta m}{3600}v\alpha \quad (12)$$

And the acceleration time from 0-100km/h is calculated as:

$$t = \int_0^{100/3.6} \frac{\delta m}{F_t - 0.5 C_d A_a u^2 - mgf} du \quad (13)$$

where δ is the vehicle rotational inertia as expressed in Eq.14, and F_t is the driving force when travelling.

$$\delta = 1 + \frac{I_w}{mr^2} + \frac{f i^2 i_0^2 \eta_t}{mr^2} \quad (14)$$

The motor operating efficiency is obtained through the interpolation of the motor speed and motor torque for the four selected driving cycles respectively. The average efficiency is set as another economic target, and it is expressed as:

$$\eta_{avg} = \frac{\sum \eta_{motor}}{n_{points}} \quad (15)$$

where η_{avg} is the average efficiency, n_{points} is the number of points and η_{motor} refers to the corresponding motor efficiency.

The objective function takes into account the economic performance in terms of the sum of the power demand together with the sum of the average efficiency of the selected driving cycles, and the dynamic performance in terms of the acceleration time. The weightings between the sum of power demand, the acceleration time, and the sum of average motor efficiency in the objective function are 0.4,0.3 and 0.3. The optimization process is illustrated in Fig.2.

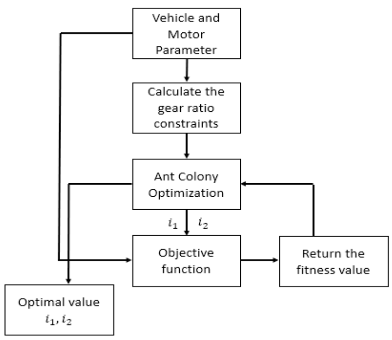

Fig.2. Optimization process

5. Simulation

In this study, the ACO algorithm was utilized to optimize the gear ratios for a two-speed DCT PEV model. The resulting optimized gear ratios were found to be 3.3078 and 1.7093, while the previous gear ratios are 2.6 and 1.8 separately. The PEV model was developed in MATLAB/Simulink, which includes the driver's model, two-speed DCT as illustrated in Fig.3, motor along with battery model, and vehicle dynamic model. The testing is achieved by simulating the EV model under the NEDC driving cycle. The real-time speed follows the reference speed as indicated in Fig.4, demonstrating the effectiveness of the EV model.

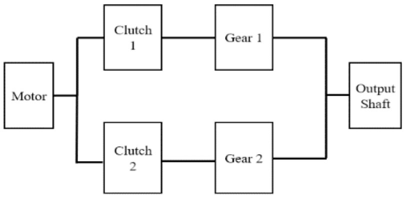

Fig.3. Two Speed DCT

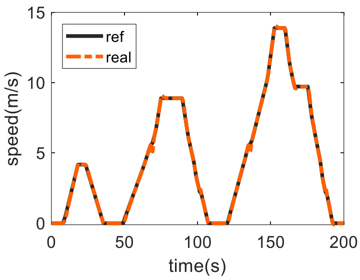

Fig.4.Real-time Speed and Reference Speed

The economic performance of the model was evaluated on the basis of the energy consumption (kWh per 100 km) and change in SOC (state of charge), while the dynamic performance was evaluated by the measurement of the acceleration time from 0 to 100 km/h. The comparison of the acceleration time and the energy consumption is indicated in Table 2. With respect to the acceleration time, it has been reduced by 41.30% from the original. A shorter acceleration time implies greater dynamics. And in the case of energy consumption, it has decreased by 16.19%. Lower energy consumption applies to lower operating costs, which reduces expenses in the long term. These results confirm the effectiveness of the optimization process where performance has been improved.

Table 2. Comparison of Results

Assessment Criteria	Previous gear ratios	Optimized gear ratios
Acceleration time	15.2032	8.9236
Energy consumption	6.228	5.22

Furthermore, regarding the SOC, the simulation result of the SOC shows that the SOC decay following the optimization, as shown in Fig. 5. It showed an improvement compared to the initial state and resulted in a higher SOC value. The variation in SOC further validates the validity of the optimization, as SOC is a common indicator of EVs to show their performance and cost and slower decay of SOC can extend the life of the battery, which generates an economic contribution to EVs.

Based on the analysis of the results, the simulation of the EV model equipped with a 2-speed DCT in NEDC driving confirms the rationale of optimizing the gear ratio using ACO by showing an improvement in terms of both economic and dynamic performance.

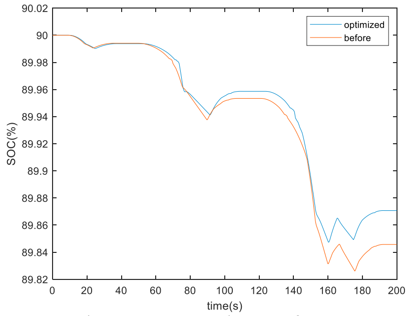

Fig.5. Comparison of SOC

6. Conclusion

To conclude, the paper analyzed the commonly used driving cycles and obtained their characteristics, such as maximum speed and power demand, which are applied to the determination of the basic indicators of vehicle performance and the design of the gear ratios. ACO, an optimization algorithm in computer intelligence, is applied to optimize transmission ratios based on calculated constraints, considering economic and dynamic aspects as an objective function with respect to the sum of power demand as well as the sum of average motor efficiency of the selected driving cycles, and the acceleration time from 0 to 100 km/h on flat roads. A simulation EV model is developed, and the simulation results are evaluated through the acceleration time, energy consumption and the change of SOC. These results demonstrate a satisfactory enhancement in the performance compared to the previous gear ratios and confirm the validity of the optimization method which can achieve the objective of optimizing the gear ratios under various operating scenarios with enhanced vehicle economy and dynamics.

7. Acknowledgement

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