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SIZING OF POWER TRAIN AND COOLING OF THE BATTERY SYSTEMS OF HYBRID ELECTRIC VEHICLES BY USING GENETIC ALGORITHM

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Abstract

Nowadays, the development of HEVs is done from three approaches: emission, fuel consumption, and vehicle performance. Due to the expansion of the use of HEVs around the world, optimal performance of the power train and power supply in the vehicle system has become an important issue. In this paper, in the first step, an optimal cooling attempt was made during power transfer in batteries by designing battery modules and their optimal configuration. The optimal design of the components of the transmission system and their optimized sizing have been performed in such a way that, while reducing emissions and fuel consumption, the dynamic performance of the vehicle is maintained at the standard level of passenger ones. The characteristics of class B passenger vehicle were utilized for modeling and simulation of the HEV and its optimization carried out by the constrained multi-objective genetic algorithm. It has been depicted that with the simultaneous sizing of power transmission components and optimal cooling of the battery system, fuel consumption and emission can be reduced by 5% and 8%, respectively, in various cycles of driving and traffic conditions.

Keywords: Fuel consumption, emissions, power transmission structure, hybrid electric vehicle

1. Introduction

One of the issues that never occupied the minds of manufacturers in the first years of the introduction of internal combustion vehicles to the market was the many problems that over time directly or indirectly plagued the world. Problems that today require huge funds to solve them. One of these problems is air pollution and serious damage to the environment. The use of current vehicle technology has created major environmental challenges for the lives of the inhabitants of the planet. The release of toxic gases such as hydrocarbons, sulfur dioxide, carbon monoxide, and particulate matter caused by the consumption of fossil fuels in vehicles, in addition to producing acid rain, forming greenhouse gases, and damaging the ozone layer, always exposes the health of citizens [1-5], [21]. The relationship between the increase in lung cancer rates and exposure to these pollutants is one of the issues that has been investigated and proven in several studies. Another issue that calls for changes in the common technologies used in the automobile industry is the reduction of fossil fuel resources and the existence of severe price fluctuations in the market of oil and other fuel sources. Considering that what has been mentioned so far is only part of the many problems caused by internal combustion vehicles, the need to make efforts to obtain vehicles with lower fuel consumption and emissions becomes more evident.

In the previous researches investigated the effect of various hybrid vehicle performance over the traffic conditions [6-10]. In [7] they studied the optimization of powertrain size including engine, motor and batteries in vehicle performance. They found that by optimal sizing of the components the energy loss can be reduced up to 20% in the same vehicle dynamic performance. In [8] investigated the control strategy for the HEVs by using the least energy usage in real world traffic conditions. They propose the control strategy instead of on/off system for power sources, they mixed power sources (electrical and engine powers) to reach the standard vehicle performance whilst minimizing the pollution. The control strategy they have put forward is said to be capable of achieving a reduction of up to 10% in emission as well as fuel consumption as compared to the on/off system.

One of the most important issues in the application of automatic gearboxes such as AMT and CVT is the gear change strategy. Various methods have also been proposed to design the gear shifting strategy in automotive gearboxes [11-15]. Fuzzy logic has also been used to control gear shifting [16, 17]. Analytical optimization methods have also been used to optimize these strategies.

In this paper, according to the approach of improving the dynamic performance of the vehicle, first, the structure of the parallel hybrid vehicle for passenger vehicles with the aim of improving the longitudinal dynamic performance and reducing its fuel consumption is presented simultaneously, and then the selection of hybrid vehicle powertrain system components for electric hybrid vehicles is presented. In this research, the following are studied:

- Power Transmission Structure Modeling for Electric Hybrid Vehicles with the Approach of Reducing Fuel Consumption and Improving Its Dynamic Performance.
- Selection of electric hybrid vehicle powertrain system components.
- Simulation of vehicle performance using Advisor software and comparison of results in real driving cycles.

2. Modeling

In vehicle simulation using simulation software, without spending high laboratory and test costs, the sample vehicle in class B sedan is proposed, and before it reaches the production stage, we can make a general estimate of fuel consumption and pollution. And check with different cycles and measure the amount of fuel consumption and pollution with the existing standards.

Simulation of a vehicle-by-vehicle simulation software reduces a large part of the costs of testing and laboratory, but for a good simulation, we must know all the parameters affecting the vehicle and include them in the in addition, the selection of a good simulation software should be based on the simulation method in the software, which can be forward or backward or a combination of these. There are two methods, each with advantages and disadvantages that should be considered in the overall analysis of the results [18].

2.1. The structure of simulation software and its comparison

Vehicle simulation software uses two main methods in modeling a vehicle and analyzing it, which we will describe below [19, 20]:

2.1.1. Backward method

Vehicle simulators that use the backward method actually answer the question that (if we assume that a Vehicle travels a certain route, then how will the performance of each of the components be) not the behavior. Not all models require this, and the amount of force applied to accelerate the Vehicle in a given time step is calculated instead from the speed that is necessary to traverse the section of the route. Then the required force is converted into the required torque from the above components and also the linear speed is converted into rotational speed.

This method of discussion in the components of the power transmission system continues in the reverse direction of the traction power flow until the amount of fuel consumption or electric energy consumption that is needed to travel the route is calculated and then the amount of pollution of the model Vehicle per driving cycle (route) The backward method has the advantage that in order to calculate the efficiency of each component and enter it into the calculations, we can directly extract the efficiency from the relevant tables by having the torque and speed.

This advantage increases the speed in calculations using the backward method. However, the backward method considers a specific path to be traversed, when the changes in the speed or acceleration of the traversed path are more than the ability. is a power transmission system, in that case the calculations of the performance of the components will not be accurate and therefore has a weak point, and also because the map of the performance diagrams of the components is calculated in steady state, the dynamic effects are not applied and the calculations will suffer errors, and one Another weakness of the backward method is the weakness of this method in applying control parameters.

2.1.2. Forward method

The forward method of simulation also involves a driver model that factors in the required speed together with the acceptable speed of the route in order to issue a throttle and brake command. There can be a different setting for the throttle command that will set the torque output of the engine and also energy consumption rate. This torque is put into the engine in a power transfer model and will be transferred through the power transfer according to its ratio and its efficiency.

The torque calculated in the forward method is transferred directly in the direction of the physical flow of power until finally the traction force is calculated at the point of contact of the tire with the road and the final acceleration is calculated from the formula A=F/Meff. The forward method Measurable parameters in a power transmission, such as control signals and actual torque (not requested torque), enter vehicle controllers into the calculations and finally the forward method to calculate the maximum acceleration when the throttle is fully open. It is open, it is suitable. The most important weakness of the forward method is the simulation speed.

ADVISOR software is used in this project to simulate the vehicle, this software uses a combined backward and forward method which is closer to the backward method. In the next section, we will explain this software and its combined simulation method.

2.2. HEV simulation

One of the important reasons for simulating fuel consumption and pollutant production is to compare the results of vehicle performance with international standards. The use of simulation software helps to reduce the cost of periodic testing.

ADVISOR is used to simulate HEVs and buses [18] and a project comparing simulation results by software and laboratory results was conducted by Mr. Randall Domm Senger in 1998 at the University of Virginia has been published [19]. This software is very accurate in simulating the vehicle and the results obtained from it correspond to the laboratory results with high accuracy.

2.3. The impact of driving patterns, on the levels of pollution produced by vehicles

Laboratory research has been conducted in recent years on the effect of traffic and driving cycle on the rate of pollution generation and fuel consumption presented and examined the driving cycle effect and urban traffic on fuel consumption and pollutant generation [20].

In another article in the same field, with laboratory measurements, the amounts of fuel consumption and pollutants for different cycles for several sample vehicles have been determined. In the results section, the effect of the driving cycle on the amount of fuel consumption and the production of pollutants has been carefully investigated and described in detail.

2.4. Backward calculation path

On this route, which is the motion cycle, it is the point where the particular velocity is introduced into the simulation in the temporal sense. The drive cycle block passes the desired speed on to the body block. There are no performance constraints in the vehicle block [4]. For this block and using the demand speed the average traction power and the intended mean speed are estimated. The requirements come from the vehicle to the wheel/axle and its subsections. In the wheel/axle block, linear values of force and linear speed are transformed into torque and rotational speed respectively. In this block, effects of tire slippage, axle and wheel bearing friction, and the rotational inertia of wheels and a drive axle are taken into account. The tire against the weight of suspension system, the tire longitudinal power, vehicle speed and the slip friction system.

$$Slip = \omega_{whreq} \times (\frac{r_{wh}}{v_{req}} - 1) \tag{1}$$

Tire slip is allowed up to a maximum amount and this limits the traction force. The requested speed is also limited by the maximum acceleration, resulting from the traction power. The advisor software solves the motion equations together as follows to evaluate the maximum power and acceleration.

$$\frac{dv}{dt} = \frac{F}{m}$$
$$F = F_{tractive}(dv/dt) - F_{aero}(v) - F_{rolling} - F_{slope} \tag{2}$$

As can be seen in Figure 1, the shear force required to traverse the path when the staircase speed is required reaches its maximum value of 2.1*4^10. The force required decreases as the vehicle accelerates.

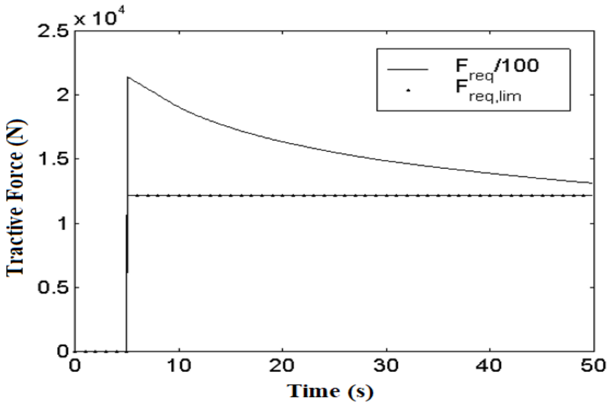

Figure 1. Variation of the requested force (Freq) and the limited requested force (Freq,lim)

2.5. Different types of power train

2.5.1. Conventional

The conventional type is an example of a passenger vehicle that is powered by a combustion engine. The structure of the powertrain system is depicted in Figure 2.

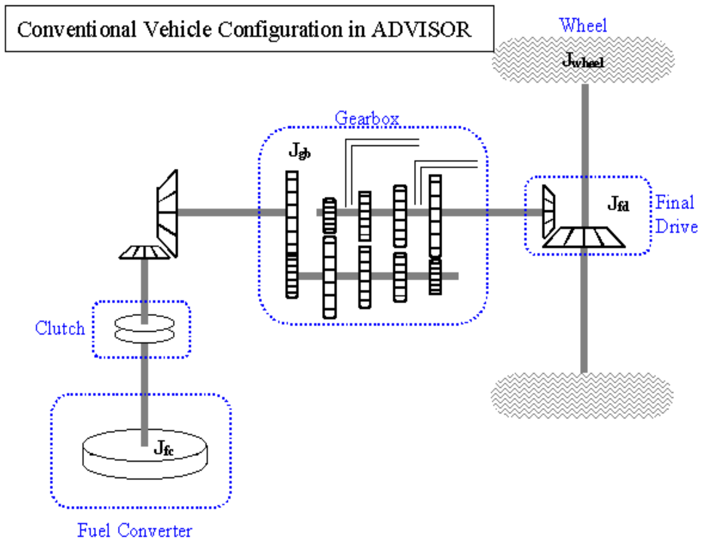

Figure 2. Power train diagram of a conventional vehicle

2.5.2. Parallel

The components include a combustion engine, a battery, and an electric motor. The name parallel derives from the fact that both the electric and combustion engines can produce the torque needed to propel the vehicle. Also, during braking mode, the combustion engine can serve as a generator to charge the battery. The structure of the parallel powertrain system is depicted in Figure 3.

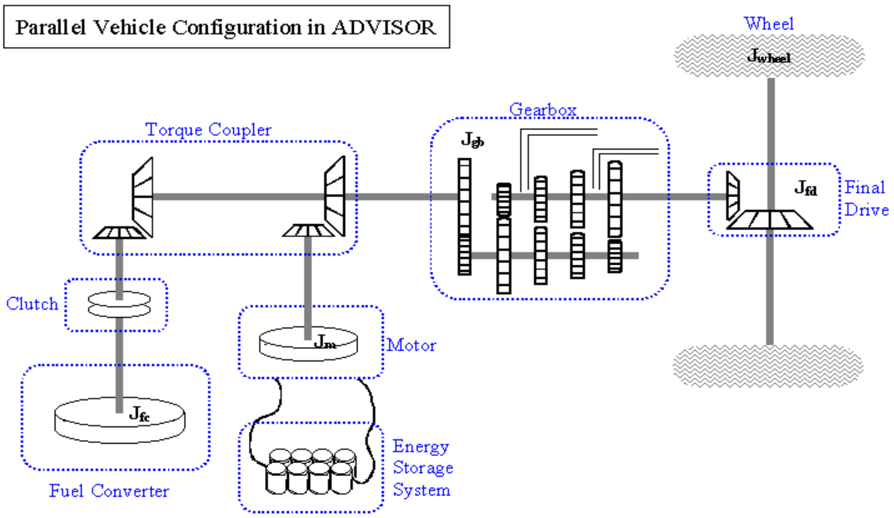

Figure 3. Power train diagram of parallel type vehicle

2.5.3. Series

Among the components of a series vehicle are: a combustion engine, generator, battery and electric motor. The combustion engine of the vehicle does not rotate the shaft of the vehicle directly. A generator is employed to convert the mechanical power into electrical power and the required torque to move the vehicle is provided by an electrical motor. Figure 4 depicts the series type power train system.

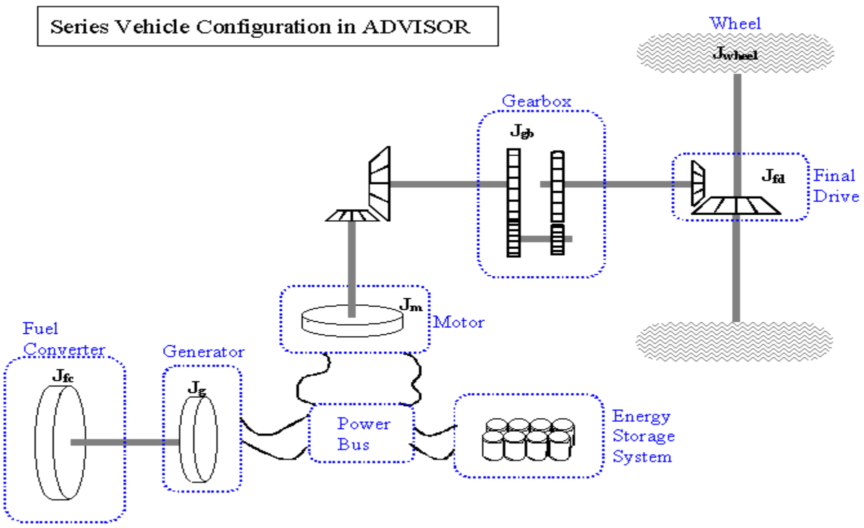

Figure 4. Power train diagram of series type vehicle

2.6. Optimization procedure

This article uses genetic algorithms (GA) as a type of meta-heuristic optimization inspired by natural selection. They are widely used to optimize the sizing of power transmission components and battery modules in hybrid electric vehicles (HEVs) and other power systems. A genetic algorithm (GA) works by mimicking the natural process of evolution. It uses techniques like selection, crossover, and mutation to refine and improve solutions to an optimization problem gradually. This approach is especially helpful for tackling complex, nonlinear, or multi-objective problems where traditional mathematical methods might fall short. Essentially, it's like letting nature-inspired processes guide us toward better solutions over time. The objective function represents the key performance metrics to optimize. These metrics include minimizing fuel consumption, reducing emissions (NOx, CO, HC), maximizing battery lifespan and optimizing powertrain efficiency. Genetic algorithm uses an iterative algorithm that can be formulated as follows:

I. Creating the initial generation (Pt, t = 0)
II. Calculation of merit values for each person of the current generation f (pi,t)
III. Selection of competent population to produce the next generation
IV. Actions of the crossover operator
V. Applying the mutation operator
VI. New generation production (Pt → Pt+1) (t → t +1)
VII. Repeat steps 2 to 6 until the loop completion condition is satisfied

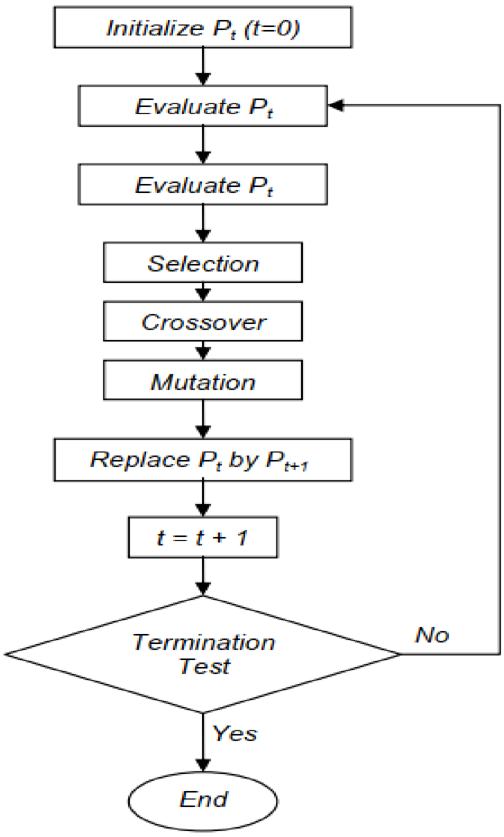

Figure 5. Flowchart of optimization

Each potential solution (an individual in the population) is represented as a chromosome, typically encoded as a vector of parameters. A set of initial solutions (individuals) is randomly generated within predefined constraints. Each individual is tested against the objective function, which calculates a fitness score based on performance criteria (e.g., fuel consumption and emissions in a driving cycle like UDDS, FTP and ECE-EUDC). Individuals with the best fitness scores are selected to reproduce. Pairs of selected individuals exchange portions of their chromosomes to create offspring. This introduces diversity while maintaining good traits. To prevent premature convergence, some genes in the new population undergo random mutation (e.g., slightly changing battery capacity or gear ratio). The process repeats over multiple generations until a stopping criterion is met. The flowchart related to the genetic algorithm is illustrated in Figure 5.

2.7. Sizing of powertrain system

To use the genetic algorithm in the optimal sizing of the HEV, the sizing problem is formulated as an optimization issue and then this optimization problem is solved with the GA. The first step in formulating the problem is determining decision variables or design variables. Here, the goal is to determine the size of the main electrical and mechanical components of the power generator. These components include combustion engine, electric motor and batteries. In the optimization process, it should be possible to change the size of these components to achieve the optimal size. To change the size of these components in the optimization process, the scaling techniques available in the ADVISOR software have been used.

To change the size of the combustion engine, first a combustion engine is considered as the base combustion engine. A scaling factor is used to change the size of this combustion engine. This coefficient, which is called Sf, changes the maximum output power of the combustion engine. To change the size of the electric motor, an electric motor is selected as a basis and then its size is changed using a scaling factor. This scaling factor is called S_m. S_b variable is used to change the battery size. These variable changes the number of battery units.

Also, optimization variables include sizing variables, which are defined as,

$$X = (Sizing \quad parameters(C_f, C_m, C_b)) \tag{3}$$

Three parameters of sizing parts are Engine scaling coefficient ($C_{f.c}$), motor controller scaling coefficient ($C_{m.c}$), and module number of batteries ($C_{b.m}$). The suggested method involves changing the parameters step by step to improve the best one. Table 3 shows the sizing variable variations domain.

Table 1. Limits for variables used in optimization

Variable/ scaling coefficient	Bounds	
	Lower	Upper
Engine ($C_{f.c}$)	0.1	1
Electric Motor ($C_{m.c}$)	0.1	1
module number ($C_{b.m}$)	20	150

Based on the explanations given above, a component sizing problem is developed as a standard constrained optimization problem:

$$J(x) \text{ is to be minimized subject to } hi(x) \leq 0, \; i = 1,2,\ldots, Ncon \qquad (4)$$
$$x \in X$$

Here x is one potential solution for the problem/ the chromosome defined above, X is the predetermined bounds of the variable which encompass its maximum, its minimum and a predetermined step value, J (x) the objective function, any inequality hi(x), where i = 1, 2,..., N, that is, N stands for the number of all inequality constraints, and where each adverb has a degree of restriction equal to 0 or less than 0, ≤ 0.

One point that should however be noted is that during the optimization, there is a control strategy in place that does not change throughout the whole process as its parameter remains constant. 60 is the assumed number of chromosomes contained in each generation, and it should be stated that the chromosomes of the first generation are selected at random and uniformly from the whole solution space. Furthermore, the number of generations is taken as 60 generations. The optimization of the function it means the change of the lowest value of the KPI against the number of generations is demonstrated in Figure 6.

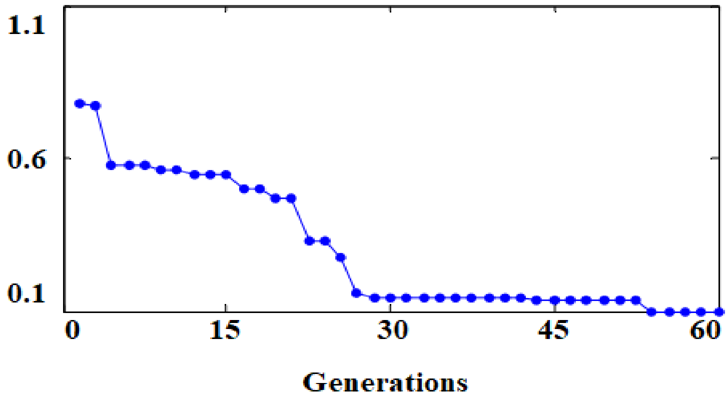

Figure 6. The process of minimizing the objective function in the process of optimizing the size of components

3. Simulation results

As mentioned in the modeling section, the traffic condition should be considered as the input of vehicle, for this purpose at first step we have extracted the driving cycles.

3.1. Driving cycle

After entering the parameters related to the vehicle (weight, length, inertia of the distance between the two wheels, and the specifications of the axles, which are considered for the class B passenger Vehicle), it is time to determine the driving cycle, which can be worked on in two ways. The use of standard and predefined driving cycles was defined [8]. The driving cycles are classified as the modal (standard) and real driving conditions. The real driving cycles are extracted from real data in the test, whilst the modal cycles are composed of the stop and go cycles which designed based on the driving conditions. In this paper the effect of both of them were investigated.

3.1.1. CYC-ECE cycle

The CYC-ECE driving cycle is a standardized test used in Europe to assess emissions and fuel consumption of light-duty vehicles and machinery under urban driving conditions. Conducted on a chassis dynamometer, this test simulates real-world city driving by incorporating frequent stops, accelerations, and decelerations, with a maximum speed of 50 km/h. Each cycle phase lasts approximately 195 seconds, covering just over one kilometer per phase. Since urban driving involves low-speed operation, frequent idling, and variable engine loads, it often leads to higher emissions of pollutants such as carbon monoxide (CO), hydrocarbons (HC), nitrogen oxides (NOx), and particulate matter (PM) due to inefficient combustion. For Hybrid Electric Vehicles (HEVs), the CYC-ECE cycle is particularly significant as the frequent braking events enhance the benefits of regenerative braking, improving overall energy efficiency. This drive cycle is also referred to as MVEG-A cycle and is composed of four ECE parts.

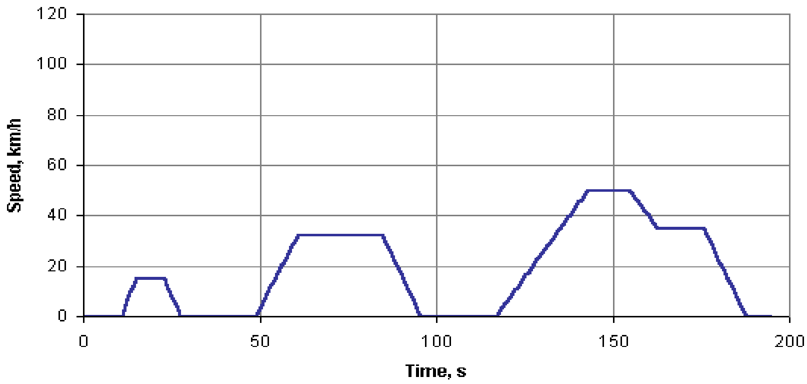

Figure 7. ECE Cycle

In this cycle, as shown in the Figure 7, the standing time is taken out and the time for the engine to start is same as time zero, and at this moment, the testing for the pollutants begins. This correction method is called the new European driving cycle or NEDC. The cis is an urban driving cycle, and also is called the UDC cycle which is employed when displaying the driving conditions of urban cities like Paris and Rome.

3.1.2. CYC- EUDC cycle

The Extra Urban Driving Cycle (EUDC) is a test used in the New European Driving Cycle (NEDC) to assess how vehicles perform under high-speed, highway-like conditions. It lasts 400 seconds (about 6 minutes and 40 seconds) and covers a distance of 6.96 kilometers, with speeds reaching up to 120 km/h. Unlike city driving, which involves frequent stops and slow speeds, the EUDC includes rapid accelerations, steady cruising, and occasional deceleration, mimicking real-world highway driving. Because of the higher speeds and engine loads, vehicles tend to consume more fuel and produce higher emissions, particularly nitrogen oxides (NOx) and carbon monoxide (CO). For Hybrid Electric Vehicles (HEVs), this driving cycle presents unique challenges, as the limited braking opportunities reduce the benefits of regenerative braking, forcing the vehicle to rely more on the internal combustion engine (ICE). This makes battery management and powertrain optimization crucial to maintaining efficiency. You can have a glance at the diagram of the EUDC cycle in Figure 8. In Table 2, the features of both ECE and EUDC cycles can be compared.

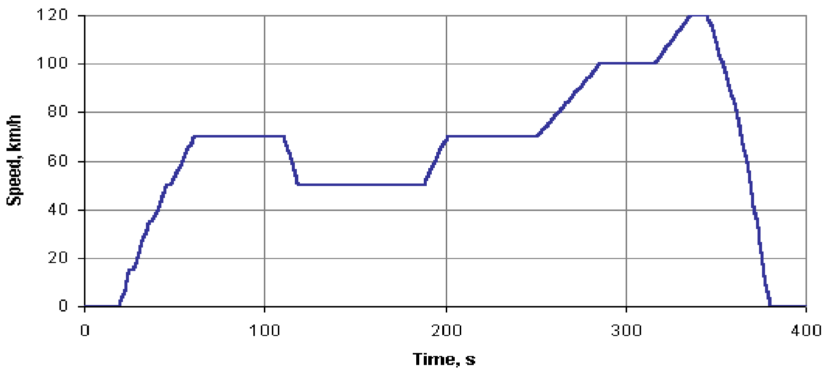

Figure 8. EUDC Cycle

Table 2. Specifications of ECE 15 EUDC cycle

Features	Unit	ECE 15	EUDC
Distance	km	4.10	7.00
Duration	time	790	405
Average Speed	km/h	18.8 (with idling)	62.5
Maximum Speed	km/h	60	120

3.1.3. UDDS cycle

As illustrated in Figure 9, this cycle is commonly known as the federal test procedure cycle. The cycle accurately represents urban driving conditions on roads which are 12.07km long with recurring halts. Its maximum speed is 91.2 kilometers per hour while the average speed is 31.5 kilometers per hour. It has two separate stages:

a) 505 seconds (5.78 km at mean velocity of 41.2 km),
b) 864 seconds.

The first phase is from the cold engine and there is a ten-minute break in between the two phases. The respective values for first and second phases are 0.43 and 0.57 and these are also quoted for the United States.

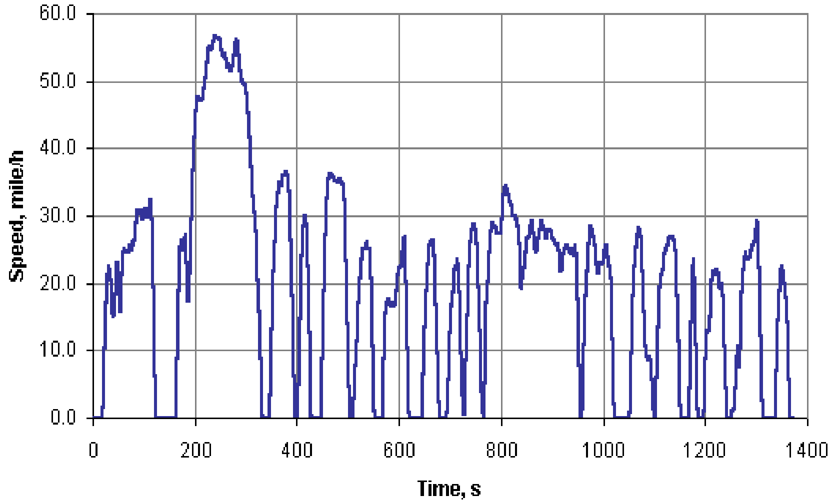

Figure 9. UDDS Cycle

3.1.4. FTP cycle

FTP cycle including phase one and two which shown in Figure 10. This cycle is extracted from real driving conditions in USA and present the real traffic condition of the city for 2500 seconds.

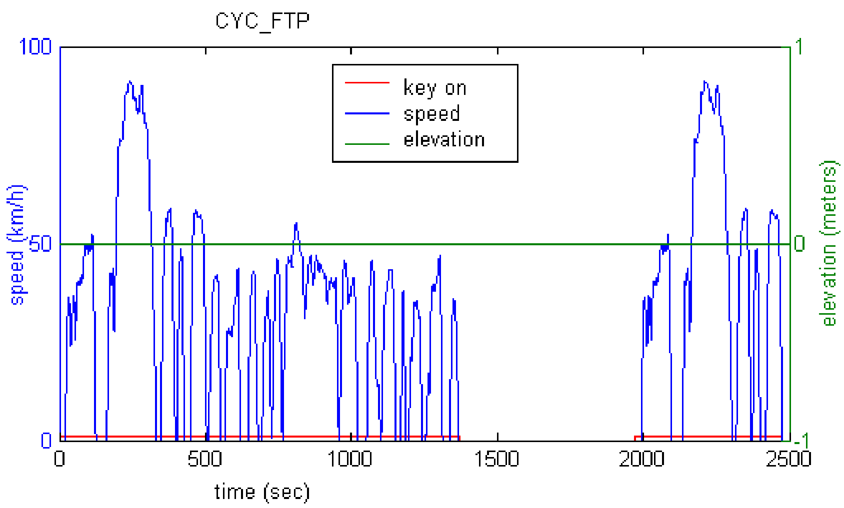

Figure 10. FTP Cycle.

In the subsequent step, the outcomes of the HEV simulation with the various driving cycles as inputs have been analyzed, and finally, the influence that the transmission configuration has on the operational characteristics of the vehicle has been examined. The different cycles for which the simulation results pertaining to the HEV are presented in the Table 3 and Table 4 respectively.

Table 3. FTP cycle specifications

Structure	Hc (g/Km)	Co (g/Km)	Nox (g/Km)	Pm (g/Km)	L100 (L/100Km)	Gasoline eq. (L/100Km)	Distance (Km)
Parallel	89.927	1.597	221.819	0	56.6	63.6	3.5
Series	54.539	0.223	176.452	0	36	40.5	3.5

Table 4. UDDS cycle specifications

Structure	Hc (g/Km)	Co (g/Km)	Nox (g/Km)	Pm (g/Km)	L100 (L/100Km)	Gasoline eq. (L/100Km)	Distance (Km)
Parallel	37.285	2.359	96.248	0	46.7	52.5	8.9
Series	22.798	1.398	74.758	0	31.3	35.2	8.9

A closer analysis of fuel consumption and emissions data reveals that the parallel hybrid structure demonstrates superior efficiency compared to the series hybrid structure. This difference arises primarily from the energy conversion process in each configuration. In a series hybrid system, the internal combustion engine (ICE) generates electricity through a generator, which then powers an electric motor to drive the wheels. This additional conversion step introduces energy losses in the generator, power electronics, and motor, leading to higher fuel consumption and emissions. In contrast, the parallel hybrid system allows both the ICE and electric motor to drive the wheels directly, minimizing conversion losses and improving overall efficiency. Additionally, the series hybrid system incurs a higher initial cost due to the need for an additional generator and power electronics components, whereas the parallel system eliminates this requirement, reducing system cost. However, the parallel structure necessitates a more complex energy management system, as power must be dynamically distributed between the engine and electric motor based on driving conditions, battery charge level, and power demand. This complexity requires advanced control algorithms to optimize energy distribution while maintaining smooth operation. In contrast, the series hybrid system simplifies power management by using the engine solely as a generator, making it easier to control but less efficient overall. These findings suggest that the parallel hybrid configuration is more suitable for applications where fuel efficiency and emissions reduction are the primary objectives, whereas the series hybrid structure may be preferable for scenarios that prioritize simpler energy management, such as range-extended electric vehicles (REEVs) or low-speed driving environments.

3.2. Optimization results

Vehicle performance, fuel consumption, and emissions can be evaluated using a driving cycle, which simulates real-world driving scenarios in a controlled setting. For Hybrid Electric Vehicles (HEVs), this involves modeling the power transmission system with inputs like the battery and alternator, while outputs include parameters like acceleration, fuel consumption, and overall dynamic performance. This method provides valuable insights into how well the vehicle performs and its environmental impact under different driving conditions. However, it's important to note that when trying to optimize multiple parameters simultaneously, the impact on reducing NOx emissions can be limited. For example, during the Texas Transportation Institute Urban Bus Driving Cycle (also known as the FTP), such optimizations might not significantly lower NOx emissions and, in some cases, could even cause a slight increase in emissions by up to 1%. This suggests that while optimizing efficiency and fuel consumption is beneficial, additional strategies focused specifically on emissions control are necessary, especially in urban driving conditions, to effectively reduce pollutants like NOx.

The values of fuel consumption and pollutants of the optimized HEV with the specifications listed in Table 5 and the parameters of the sized are considered for the three cycles mentioned in Table 6.

To adjust the constituents, control of the mechanisms of the components of the HEV was done with the aid of the electric assistance control strategy. In this part of the strategy section, the results for a multiple cycles test have been verified using the previously determined optimal size of the components. The optimal working point is when the current speed doesn't change and a value of instantaneous objective function is much lower at these points than other points. Hence, it is possible to find the optimal working points for all engine speeds there are. If all these points are plotted and connected, the engine working curve can be deduced. The combustion encompassed within the engine and parameters recorded in the objective function determine how the curve is shaped. Energy consumption and efficiency with optimal and initial state is shown in Table 7.

Table 5. Specification of optimized HEV

Variable	Amount
Total Mass	1070
Gearbox	5 speed with 98% efficacy
ICE	SI fuel convertor, max power: 56 kw
EM	AC motor, Max power: 28 Kw
Battery system	Lithium-ion, 55 AH; weight 4.8kg
Modules number	44
S_f, S_m, S_b	1.1; 0.89; 0.9

Table 6. The fuel use and emissions for the optimized HEV across different cycles

Variable	FTP	UDDS	ECE-EUDC
Equivalent Fuel (L/100km)	5.34	4.98	5.73
Emission HC (g/km)	0.29	0.32	0.37
Emission CO (g/km)	1.14	1.04	1.51
Emission Nox (g/km)	0.22	0.19	0.23
Objective value	1.61	1.52	1.87

Table 7. Comparison of energy consumption and efficiency in optimal and initial state

<table>
<tr><th colspan="9">Optimized (Initial) optimization</th></tr>
<tr><th colspan="5">Power</th><th colspan="4">Save</th></tr>
<tr><th></th><th>In</th><th>Out</th><th>Loss</th><th>Eff.</th><th>In</th><th>Out</th><th>Loss</th><th>Eff.</th></tr>
<tr><td>Fuel convertor</td><td>18256 (23420)</td><td>6104 (6131)</td><td>12151 (17289)</td><td>0.33 (0.26)</td><td></td><td></td><td>0 (495)</td><td></td></tr>
<tr><td>Battery</td><td>2503 (1531)</td><td>2903 (2301)</td><td>589 (341)</td><td>0.84 (0.84)</td><td>11077</td><td></td><td></td><td></td></tr>
<tr><td>EM</td><td>2860 (2499)</td><td>2439 (2091)</td><td>421 (427)</td><td>0.86 (0.82)</td><td>2601 (2001)</td><td>2209 (1643)</td><td>401 (302)</td><td>0.86 (0.86)</td></tr>
</table>

Train	5403 (5498)	5130 (5150)	271 (289)	0.96 (0.95)	1098 (1010)	1101 (971)	93 (59)	0.93 (0.92)
Final drive	5130 (5150)	5130 (5150)	0	1	1101	1101	0	1
Auxiliary forces	1301		1301					
Resistance forces			2421					

4. Conclusion

This paper investigates the impact of power transmission structure sizing within real driving cycles on the performance of hybrid electric vehicles (HEVs). The findings highlight that optimized sizing contributes significantly to fuel efficiency, primarily due to advanced energy management systems that regulate power distribution effectively. By strategically utilizing electric propulsion at low speeds and during stop-and-go conditions, HEVs substantially reduce fuel consumption and greenhouse gas emissions. This optimization not only enhances overall energy efficiency but also mitigates environmental pollution, making HEVs a more sustainable alternative to conventional internal combustion engine vehicles, particularly in urban and high-traffic scenarios. Furthermore, the results underscore the economic benefits of HEVs, as reliance on electric propulsion in specific driving conditions leads to notable reductions in fuel costs. These advantages reinforce the importance of refining HEV powertrain architectures to maximize efficiency while minimizing environmental impact. However, while this study focuses on power transmission structure sizing, further research is needed to explore the role of control systems and the optimization of power transmission components in alternative vehicle architectures. Future investigations could examine the interplay between different drivetrain configurations and energy management strategies to enhance HEV performance across diverse driving conditions. Additionally, incorporating real-world driving data and advanced machine learning algorithms could provide deeper insights into optimizing powertrain efficiency.

References

[1] Ruan, J., Walker, P.D., Zhang, N., Wu, J., “An investigation of hybrid energy storage system in multi-speed electric vehicle”, Energy 140 (2017) : 291-306.

[2] Ruan, J., Walker, P., Zhang, N., “A comparative study energy consumption and costs of battery electric vehicle transmissions”, Applied energy 165 (2016) : 119-134.

[3] Ahmadi, S., Bathaee, S.M.T., Hosseinpour, A.H., “Improving fuel economy and performance of a fuel-cell hybrid electric vehicle (fuel-cell, battery, and ultra-capacitor) using optimized energy management strategy”, Energy Conversion and Management 160 (2018) : 74-84.

[4] Madanipour, V., Montazeri-Gh, M., Mahmoodi-k, M., “Optimization of the component sizing for a plug-in hybrid electric vehicle using a genetic algorithm”, Proceedings of the institution of mechanical engineers, Part D: journal of automobile engineering 230(5) (2016) : 692-708.

[5] Mazouzi, A., Hadroug, N., Alayed, W., Hafaifa, A., Iratni, A., Kouzou, A. “Comprehensive optimization of fuzzy logic-based energy management system for fuel-cell hybrid electric vehicle using genetic algorithm”, International Journal of Hydrogen Energy 81 (2024) : 889-905.

[6] Tran, D.D., Vafaeipour, M., El Baghdadi, M., Barrero, R., Van Mierlo, J., Hegazy, O., “Thorough state-of-the-art analysis of electric and hybrid vehicle powertrains: Topologies and integrated energy management strategies”, Renewable and Sustainable Energy Reviews 119 (2020) : 109596.

[7] Nguyen-Minh, T., Nguyễn, B.H., Vo-Duy, T., Ta, M.C., Trovão, J.P.F., Antunes, C.H., “A universal optimal sizing for hybrid energy storage system of electric vehicles”, Journal of Energy Storage 92 (2024) : 112128.

[8] Chen, S.Y., Wu, C.H., Hung, Y.H., Chung, C.T., “Optimal strategies of energy management integrated with transmission control for a hybrid electric vehicle using dynamic particle swarm optimization”, Energy 160 (2018) : 154-170.

[9] Nainggolan, N., Maghsoudlou, E., AlWadi, B.M., Atamurotov, F., Kosov, M., Putra, W., “Advancements in Optimization for Automotive Manufacturing: Hybrid Approaches and Machine Learning”, International Journal of Industrial Engineering and Management 15(3) (2024) : 254-263.

[10] Liu, H., Han, L., Cao, Y., “Improving transmission efficiency and reducing energy consumption with automotive continuously variable transmission: A model prediction comprehensive optimization approach”, Applied Energy 274 (2020) : 115303.

[11] Luo, Y., Chen, T., Zhang, S., Li, K. “Intelligent hybrid electric vehicle ACC with coordinated control of tracking ability, fuel economy, and ride comfort”, IEEE Transactions on Intelligent Transportation Systems 16(4) (2015) : 2303-2308.

[12] Das, H.S., Tan, C.W., Yatim, A.H.M., “Fuel cell hybrid electric vehicles: A review on power conditioning units and topologies”, Renewable and Sustainable Energy Reviews 76 (2017) : 268-291.

[13] Montazeri-Gh, M., Mahmoodi-K, M., “Optimized predictive energy management of plug-in hybrid electric vehicle based on traffic condition”, Journal of cleaner production 139 (2016) : 935-948.

[14] Montazeri-Gh, M., Pourbafarani, Z., Mahmoodi-k, M., “Comparative study of different types of PHEV optimal control strategies in real-world conditions”, Proceedings of the Institution of Mechanical Engineers, Part D: Journal of Automobile Engineering 232(12) (2018) : 1597-1610.

[15] Anselma, P.G., Niutta, C.B., Mainini, L., Belingardi, G., “Multidisciplinary design optimization for hybrid electric vehicles: component sizing and multi-fidelity frontal crashworthiness”, Structural and Multidisciplinary Optimization 62 (2020) : 2149-2166.

[16] Park, S., Ahn, C., “Power management controller for a hybrid electric vehicle with predicted future acceleration”, IEEE Transactions on Vehicular Technology 68(11) (2019) : 10477-10488.

[17] Huang, Y., Wang, H., Khajepour, A., Li, B., Ji, J., Zhao, K., Hu, C., "A review of power management strategies and component sizing methods for hybrid vehicles", Renewable and Sustainable Energy Reviews 96 (2018) : 132-144.

[18] Cai, Y., Ouyang, M.G., Yang, F., "Impact of power split configurations on fuel consumption and battery degradation in plug-in hybrid electric city buses", Applied Energy 188 (2017) : 257-269.

[19] Mayyas, A.R.O., Kumar, S., Pisu, P., Rios, J., Jethani, P., "Model-based design validation for advanced energy management strategies for electrified hybrid power trains using innovative vehicle hardware in the loop (VHIL) approach", Applied Energy 204 (2017) : 287-302.

[20] Yang, R., Yang, X., Huang, W., Zhang, S., "Energy management of the power-split hybrid electric city bus based on the stochastic model predictive control", IEEE Access 9 (2020) : 2055-2071.

[21] Dindar, S., "A Comprehensive Analysis of Strategies, Challenges and Policies on Turkish Sustainable Energy Development". Journal of Engineering Technology and Applied Sciences 7(3) (2022) : 231-250.