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Novel strategies to reduce engine emissions and improve energy efficiency in hybrid vehicles

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ABSTRACT

Hybrid electric vehicles (HEV) can provide a same power as gasoline and diesel-powered vehicles while also reducing fuel consumption by 40–50%. However, due to a complex system of HEV, the power control strategies are used to improve the work efficiency, fuel economy and to reduce exhaust emissions. In the present work, four parameters are studied with the main focus on the optimization of power system of a parallel hybrid vehicle. These parameters are the influence of fuzzy logic algorithm on hybrid electric vehicle power train that is acceleration performance, climbing performance, engine efficiency and exhaust gas emissions. First, the vehicle's power train is optimized using the Advanced Vehicle Simulator (ADVISOR). Secondly, by ensuring acceleration and climbing performance, the vehicle manufacturing cost is reduced by reducing the weight of the vehicle. Thirdly, two driving road test conditions, Extra-Urban Driving Cycle (EUDC) and Urban Dynamometer Driving Schedule (UDDS) are used to enhance the fuel consumption efficiency of the vehicle. Using a fuzzy logic algorithm for random operations, the operating range of an internal combustion engine is controlled as much as possible in the most efficient range. Through the control of 121 different algorithms, the operating efficiency of the powertrain is optimized to reduce exhaust emissions and improve fuel efficiency. The results showed that the proposed strategy can reduce fuel consumption by 5%, CO by 50% and improved the operating efficiency of engine by 15%. Not only this control strategy optimizes the efficiency of powertrain, but also the efficiency of the internal combustion engine. Moreover, the motor and battery pack itself can be optimized. These hybrid vehicles can minimize the fuel demand and are the best substitute for the classic internal combustion engines.

1. Introduction

With the increasing demand of fuel and environmental restrictions on exhaust emissions, it has become necessary to strive for new solutions in the transportation system (Hu et al., 2017, 2019). Vehicle exhaust emissions are one of the essential causes of air pollution. The main component of vehicle exhaust emissions is carbon monoxide (CO) that is the leading cause of the greenhouse effect. Various countries are now proposing targeted plans for carbon monoxide reduction. European Union aims to reduce the greenhouse gas emissions to zero value and to make a neutral climate by 2050. The evolution of society having climate-neutral is a crucial challenge and a chance to shape a better future. In order to fulfil this mission, EU countries need to invest in green technologies and eliminate emissions (Union, 2021). The control targets for carbon dioxide emissions from various countries have resulted in the reduction of carbon dioxide and this decline is year by year. For example, China has controlled carbon dioxide emissions from 190 to 166 g per 100 km while the United States (US) has controlled carbon dioxide from 200 to 140 g per 100 km during the last five years (Yang, 2017).

The restrictions on carbon monoxide (CO) emissions in different

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countries are becoming stricter, therefore, different auto manufacturers need to propose more solutions to solve this problem (Hu et al., 2020). Many car manufacturers in Europe choose to use diesel engines instead of gasoline engines as they provide more torque and are much more thermally efficient than gasoline engines. However, diesel engines have problems such as relatively complicated structure, high design cost (Chakrabarti et al., 2019) and high engine noise (Kong et al., 2019). To control the problems produced by conventional vehicles, the arrival of electrical vehicles gives a persuasive approach (Li et al., 2019). Nowadays, many countries are beginning to estimate the production of hybrid electric vehicles by automobile companies. Electricity is a renewable and clean energy source. At the same time, the car does not produce any harmful gases during the use of electrical energy (Li et al., 2020).

Hybrid system vehicles of different systems can reduce exhaust emissions and improve fuel economy compared to gasoline powered vehicles and diesel-powered vehicles. However, to make them three central power system containing electric motors, battery packs and internal combustion engines to operate them in high-efficiency zones, became a significant issue for different automotive companies. Hybrid electric vehicles can be classified in many ways. According to the architectural form of the hybrid electric vehicle powertrain, they can be divided into a series hybrid electric vehicle, parallel hybrid electric vehicle and a series-parallel hybrid electric vehicle (Das et al., 2017). The series hybrid vehicle has the simplest structure and is mainly composed of three powertrains; engine, generator and electric motor (Shabbir and Evangelou, 2019). For example, BMW i3 is a series hybrid vehicle production with a Range Extender. However, this vehicle has the lowest efficiency than other types (Das et al., 2017).

In the case of a parallel hybrid vehicle, the internal combustion engine directly drives the hybrid electric vehicle through the transmission system, indirectly driving the generator to charge the battery (Karaoğlan et al., 2019). The parallel hybrid electric vehicle can flexibly arrange the power output and improve the efficiency of the power system. Honda and Mercedes's manufacturers have used the technology of parallel hybrid in Honda Insight and Benz S400 Blue Hybrid. In the series-parallel case, the hybrid drive system is a combination of series and parallel. Toyota, Nisan and Ford models of 2007 are the examples of series-parallel vehicle. However, the system is more complicated and requires more power composite devices (Banshoya et al., 2019). There are several options for hybrid vehicle powertrain optimization that are mainly divided into two categories; HEV offline energy management and HEV online energy management strategies (Enang and Bannister, 2017). The power demand for hybrid vehicles is affected by many factors such as the need for acceleration and climbing power, demand for vehicle speed and the current road conditions. Therefore, the above two strategies; HEV offline energy management and HEV online energy management are based on ensuring the underlying driving performance of the vehicle and durability of the power system (Zhang et al., 2020). HEV offline energy management mainly consists of linear programming (Lu et al., 2019), dynamic programming (Yang et al., 2020), genetic algorithms (Liu et al., 2018) and particle swarm algorithm (Enang and Bannister, 2017).

On the other hand, the HEV online energy management strategies consist of two major components; rule-based control strategies and online optimization-based strategies (Wang et al., 2019). It can be used in real-time and optimized without testing (Luo et al., 2019). Rule-based control strategies further consist of two different optimization strategies including; deterministic rule-based energy management strategy and fuzzy rule-based control strategy. The deterministic rule-based energy management strategy optimizes the known engine fuel efficiency or its exhaust emissions, but to guarantee the accurate function of the algorithm; this strategy needs precise adjustment of entire controlling parameters. In order to cover this, the instantaneous optimization procedure was used based on the extreme seeking algorithm (Dinçmen and Güvenç, 2012). Fuzzy rule-based control strategies are based on multi-valued logic and use fuzzy sets to study the science of fuzzy thinking, language forms and their laws. It analyses real-time data based on previous experience. This is a way of simulating human thinking.

Through the fuzzy logic algorithm, the fuzzification problem can be better solved and the results obtained by this are more accurate (Dawei et al., 2017). The predictive fuzzy control strategy usually works through the aid of Global Positioning System (GPS), due to which the road ahead is judged in advance and the known road conditions select the adequate options of the power system. The system can pre-determine the working mode of the internal combustion engine and choose whether to assist the acceleration by the motor or whether to charge the battery pack in advance (Enang and Bannister, 2017). Fuzzy logic algorithms are widely used in hybrid vehicle power systems (Gujarathi et al., 2017). A study carried by (Fu et al., 2012) shown that for a parallel hybrid car, the use of a fuzzy logic algorithm can effectively improve the fuel economy of the engine while reducing exhaust emissions. However, the study did not reduce the fuel consumption of the hybrid electric vehicle. Furthermore, in the study of (Khoucha et al., 2019), designed a fuzzy logic controller that used a parallel hybrid Eastern system to control the angle of the internal combustion engine throttle by using a fuzzy logic controller.

The fuzzy logic algorithm can be used not only alone but also in combination with other algorithms. In the study by (Zhou et al., 2011), they combined fuzzy logic algorithms with Particle Swarm Optimization (PSO) algorithms. In his work (Ma et al., 2019a,b) established fuzzy logic controller using New European Driving Cycle (NEDC) and Worldwide Harmonized Light Vehicles Test Cycle (WLTC) driving cycles. In another work (Gao et al., 2019), the fuzzy inference is used along with neuro-fuzzy controller, while in the work of (Sheng et al., 2019) PHEV was modelled by optimising basic fuzzy controller to an improved adaptive genetic algorithm. Fuzzy logic algorithms are more cost-effective than other algorithms. Its calculation process is more straightforward than other optimization algorithms and does not burden the powertrain of the hybrid passenger vehicle. At the same time, the fuzzy logic algorithm can ensure the accuracy of the results. By using the fuzzy logic algorithm, the internal combustion engine working range can be controlled in a high-speed range. This can help the internal combustion engine work more efficiently with the same power output.

Through the study of a hybrid vehicle power system and previous researches about optimization on a fuzzy logic algorithm, it is clear that this algorithm can improve the fuel economy (Singh et al., 2020) and fewer exhaust emissions of a hybrid vehicle. It also shows that the parallel hybrid system can provide better fuel economy than the series hybrid electric vehicle and a series-parallel hybrid electric vehicles' power system. If the internal combustion engine is only in the dynamic working range for a long time, it can reduce the exhaust emissions; however, it cannot be proved that it can have a better fuel economy. The primary mode of operation of a series hybrid system is that the internal combustion engine maintains a dynamic operating range to provide power to the motor or battery pack, but the internal combustion engine cannot provide other working paths.

Therefore, the present research is focused on optimising the fuzzy logic algorithm for a parallel hybrid vehicle system. From the previous literature, it is clear that researchers mostly worked on two or three parameters. While in this work, four parameters are studied; fuel consumption, exhaust emissions, engine efficiency and acceleration performance, with the main focus on optimization of the power system of a parallel hybrid vehicle. The reason behind considering these parameters is that these are the key indicators of an efficient vehicle. Following steps describe the summary of this work. The first step was to optimize the vehicle's raw data by using Advanced Vehicle Simulator (ADVISOR). The second step was to choose a suitable battery pack for the engine. The third step was to check the fuel consumption efficiency of the vehicle by running Extra Urban Driving Cycle (EUDC) and Urban Dynamometer Driving Schedule (UDDS) test road conditions. In the final step, the engine's powertrain was strategically optimized to reduce vehicle exhaust emissions using a fuzzy logic algorithm.

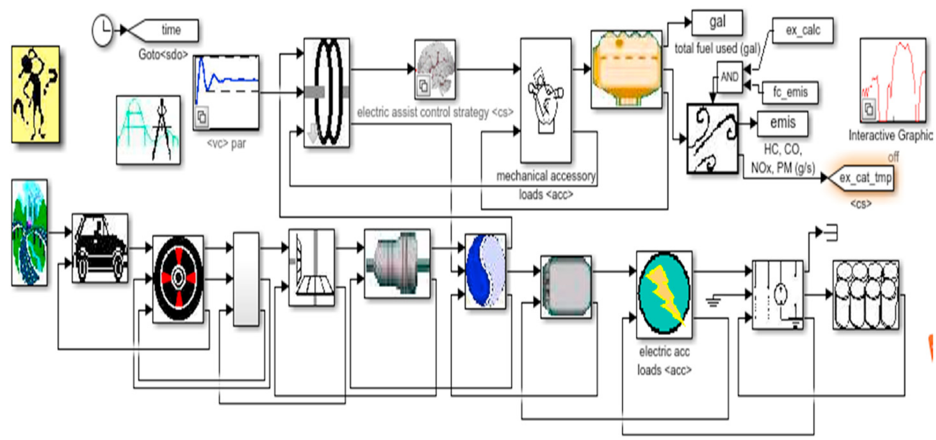

Fig. 1. ADVISOR block diagram for a hybrid electric vehicle.

2. Model configuration and simulation

In this study, ADVISOR parallel hybrid system is used for optimization. ADVISOR is car test software developed on a software named MATLAB. Block diagram of ADVISOR in MATLAB is shown in Fig. 1. It can accurately simulate the powertrain of a car. By using this software, the changes of data before and after optimization can easily be visualized. The parallel hybrid vehicle powertrain consists of several components. They are engine module, motor module, battery module, control strategy module, vehicle control module, mechanical accessories, fuel converter, exhaust system, energy storage and electric accessories load. The specific composition is similar to the work of (Babu and Ashok, 2015). The main power output of the car comes from the internal combustion engine and the electric motor. The motor is mainly used to provide auxiliary power to the vehicle. When the hybrid electric vehicle is in the process of cold start, the internal combustion engine does not participate in the work, and the electric motor starts the vehicle. Therefore, generally at low speeds, the internal combustion engine is in an efficient operating range to provide power output to the motor or battery pack. When the motor has enough driving force to drive the hybrid electric vehicle, the internal combustion engine will choose to close. In this case, the car can achieve zero exhaust emissions and zero fuel use.

2.1. Parallel hybrid electric vehicle model

2.1.1. Vehicle model

The vehicle module is the vehicle dynamics module. The actual vehicle speed and the driving force required by the vehicle are calculated from the vehicle dynamics balance equation based on the parameters of the vehicle. Eq. (1) is the average speed relation, where V_0 is the initial velocity of the simulation time step, V is the end speed of the simulation time step. In the vehicle system, when the car is climbing, the resistance of the car is mainly composed of rolling resistance, air resistance, slope resistance and acceleration resistance as follows in Eq. (2) (Ehsani et al., 2018). Where F_f is the rolling resistance, F_w is air resistance, F_i is the slope resistance, F_j is the acceleration resistance. The relation for rolling resistance is Eq. (3). Where m is the total mass of the car and g is the acceleration of gravity, f_1 and f_2 are the rolling resistance coefficients at the front and rear wheels, whereas, α is the angle of the current slope.

$$\overline{v} = \frac{v_o + v}{2} \tag{1}$$

$$F_t = F_f + F_w + F_i + F_j \tag{2}$$

$$F_f = mg(f_1 + f_2\overline{v})\cos\alpha \tag{3}$$

The air resistance can be calculated as Eq. (4) (Ehsani et al., 2018). Where C_D is the air resistance coefficient, ρ is air density and A is the windward area, which is the projected area of the car's direction of travel. The slope resistance is as follows Eq. (5). Acceleration resistance is the inertial force when the car accelerates and overcomes its mass acceleration motion. It consists of the inertial force generated by the translational mass and the inertial force generated by the rotational mass. For ease of calculation, the inertial force of the rotating part is ignored as follows Eq. (6). Through the combination of the several above relations, the complete vehicle component of the parallel hybrid system vehicle is obtained as shown in Eq. (7).

$$F_w = \frac{1}{2}C_D A\rho\overline{v}^2 \tag{4}$$

$$F_i = mg\sin\alpha \tag{5}$$

$$F_j = m\frac{dv}{dt} = m\frac{v - v_o}{dt} \tag{6}$$

$$F_t = \left(mg(f_1 + f_2\overline{v})\cos\alpha + \frac{1}{2}C_D A\rho\overline{v}^2 + mg\sin\alpha + 2m\frac{\overline{v} - v_o}{dt}\right) \tag{7}$$

2.1.2. Internal combustion engine model

The internal combustion engine module is designed based on the actual operation of the internal combustion engine. The primary function of the internal combustion engine module is to provide the required rotational speed and torque of the vehicle in the case of a simulated path and to calculate the exhaust generated during use. At the same time, the system can also show the torque that the internal combustion engine outputs to the car. The system also considers the energy loss of the internal combustion engine in actual operation. The torque of vehicle resistance is presented in Eq. (8) (Park et al., 2019).

$$T_r = \left(mgfcos\alpha + \frac{C_D A_{v^2}}{21.15} + mg\sin\alpha\right)r_w \tag{8}$$

where r_w, A and C_D are wheel radius, area and coefficient of air resistance of the vehicle.

2.1.3. The motor module

The motor module converts electricity into the torque required by the car. The module is designed based on the motor model used in the hybrid vehicle powertrain in the real world. The motor control module ensures that the controller's current does not exceed the maximum current limit and shuts down the motor when the Integrated Starter Generator (ISG) motor is not required to operate.

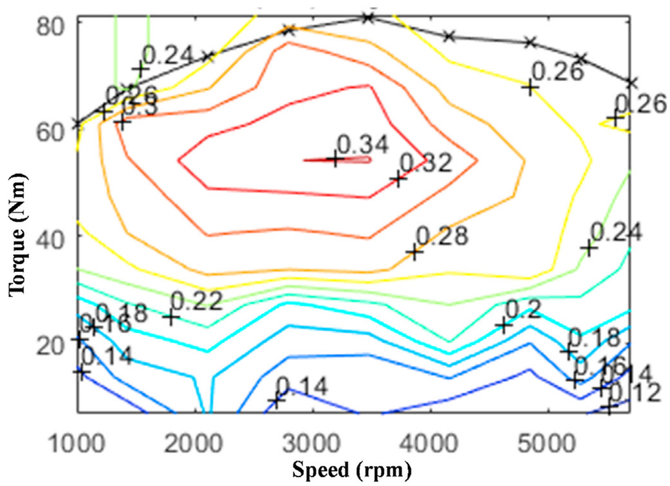

Fig. 2. Internal combustion engine efficiency map.

2.1.4. The battery pack module

The primary function of this module is to convert electrochemical energy into electrical energy. During the output process, the system can simultaneously calculate the voltage, current, and state of the battery state of charge. The design idea of this module derives from the numerical model of the nickel-metal hydride storage battery. The State of Charge (SOC) of the battery can be obtained from Eq. (9) (Hwang et al., 2020).

$$SOC = SOC_i - \frac{\int_0^t Idt}{Ah} \tag{9}$$

where SOC_i is starting value, A is the area, h is the height of battery, and I is output current.

3. Results and discussion

3.1. Motor and engine selection

The design uses a small displacement internal combustion engine that is a gasoline internal combustion engine. The emission is 1 L. The maximum output is 41 KW, whereas, the maximum working efficiency is 34% (Sheng et al., 2019). As can be seen from Fig. 2, the maximum working efficiency range of the internal combustion engine is mainly from 2000 to 4000 rpm. The choice of engine power is critical to the design of a parallel hybrid powertrain. In this design, four different battery packs (PB16, 18, 25, 28) are selected for comparison. These are the symbols used for battery packs combined in a parallel arrangement. For example, PB16 means a pack of 16 batteries in parallel and similarly PB18, PB 25 and PB28 are used for a pack of 18, 25 and 28 batteries. As can be seen from Fig. 3(a), the fuel consumption during different battery settings like battery pack (PB)16, PB18 and PB25 tests is 7 L/100 km, while PB28 has 6 L/100 km of fuel consumption. Fig. 3(b) shows a comparison of the acceleration performance of the car in the case of different battery packs through a histogram.

The 0–100 km acceleration score is the most intuitive to observe the performance changes of hybrid electric vehicles. PB16 takes 15 s, PB18 takes 10 s, PB25 takes 10.4 s whereas, PB28 takes 7.7 s to complete the acceleration process of 0–100 km/h. This study aims at ordinary domestic cars that need to have certain grade ability. Fig. 3(c) shows the climbing performance of different battery packs at 88.5 km/h. When testing with PB16 and PB18, the maximum grade is 11.9% and 20.1% respectively. Whereas, PB25 and PB28 have grades of 19.1% and 28.9% respectively. The increased power of PB25 does not reduce the impact of increased mass on vehicle performance. Exhaust emissions are one of the main criteria for choosing to use a battery pack. A comparison of the

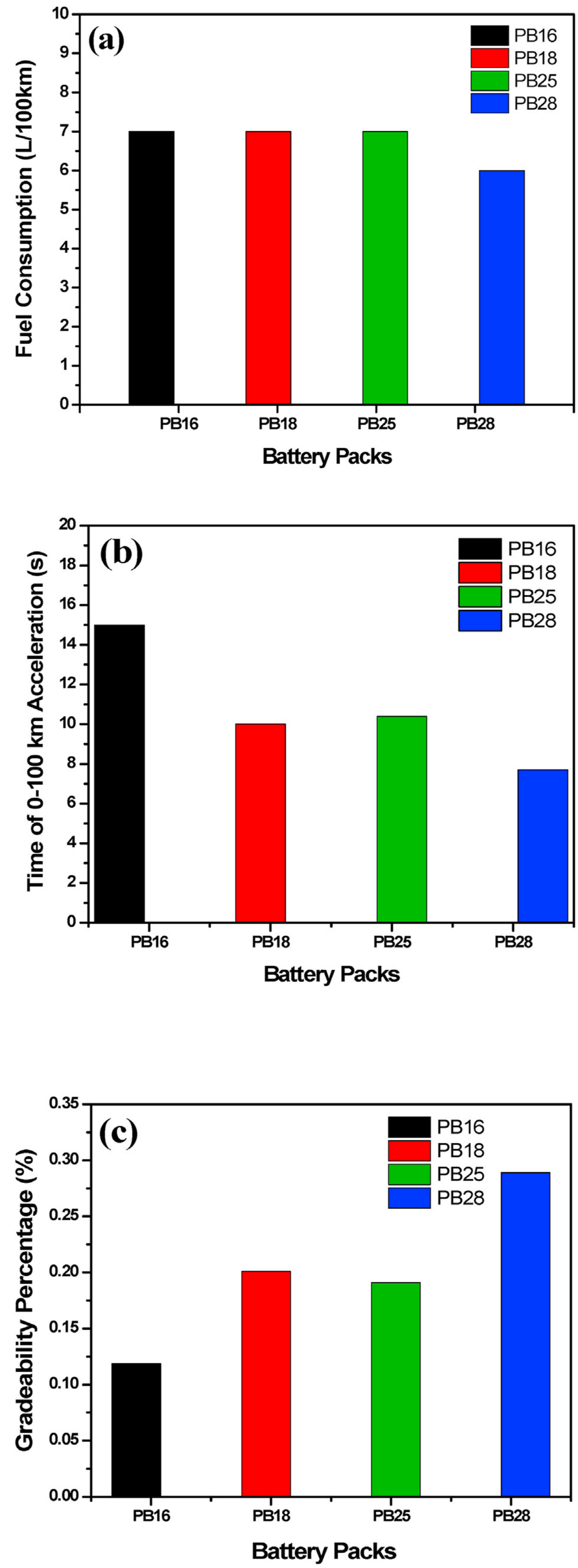

Fig. 3. Comparison of three parameters of different battery packs; (a) Fuel consumption (b) Acceleration time comparison (c) Climbing performance at 88.5 km/h.

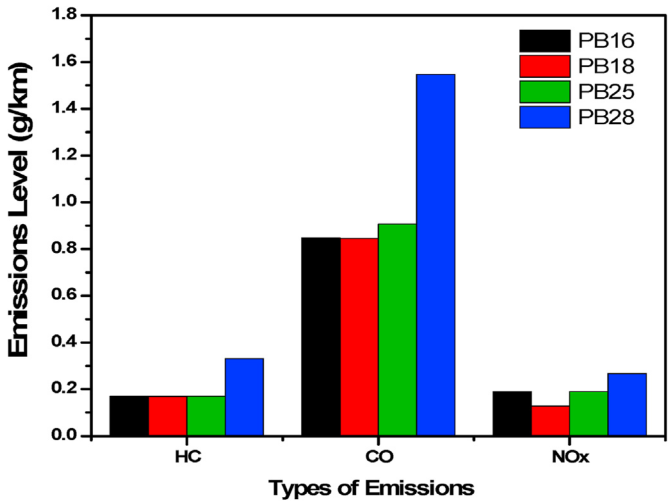

Fig. 4. Different types of emissions' levels comparison with various battery packs.

different tail gas contents produced using four different battery packs can be seen in Fig. 4. The main components of exhaust emissions are carbon dioxide, carbon monoxide, nitrogen oxides and hydroxides. This work compares the effects of different battery packs on exhaust emissions from hybrid electric vehicles by comparing carbon monoxide, nitrogen oxides and hydroxides.

The battery using PB16 and PB18 produced an average of 0.17 g/km of hydroxide, while PB25 and PB28 battery packs produced 0.17 g/km and 0.33 g/km of hydroxide that is more than PB16 and PB18 battery packs. In a carbon monoxide emission comparison, PB18 battery pack produced the lowest carbon monoxide of 0.84 g/km, whereas PB28 battery pack produced an average of twice as much carbon monoxide as the other three packs with an average of 1.55 g/km of carbon monoxide. A similar trend can be seen from the comparison of nitrogen oxides that the PB18 battery pack produced lowest of 0.13 g/km of nitrogen oxides, whereas PB28 battery packs produced the highest levels of nitrogen oxides of 0.27 g/km.

By simulating the test of four different battery packs, comparing their fuel consumption, acceleration performance, climbing performance and exhaust emissions, it is clear that PB18 is small compared to PB25. Therefore, PB18 has no problem in terms of installation. Although PB28 has better acceleration as well as climbing performance than PB18, however, its volume and weight are larger than PB18, and there are installation problems in actual use. In the powertrain efficiency comparison, the fuel consumption of PB28 was found to have the lowest fuel. However, the primary exhaust emissions of PB18 are lower than PB28. So, in summary, PB18 was chosen as the test battery pack in this simulation test.

3.2. Fuzzy logic algorithm

It is necessary to ensure that the state of charge of the battery pack is above the minimum during driving. In this test, the lowest value of the state of charge of the battery pack is 0.5. When the battery state reaches 0.75, the internal combustion engine stops to charge motor. The input mainly divides into two parts. One part is the torque required for the internal combustion engine that contains the torque summation engine available at the current speed. The other is real-time data for the battery pack state of charge. The real-time data of the two is converted into quantitative data by a converter and then input into the fuzzy logic algorithm model. The fuzzy logic algorithm determines whether the motor can participate in the work of internal combustion engine at this time by the state of charge of the receiver battery pack. Then, it determines whether the operating efficiency of the internal combustion engine is efficient by collecting the rotational speed data and torque data of the internal combustion engine (Ma et al., 2019a,b).

To make the results more accurate, the input data is quantified at 11 levels of the fuzzy logic algorithm. In the case where the battery pack is guaranteed to have a higher than the minimum state of charge, the fuzzy logic algorithm selects the optimal speed by which the internal combustion engine can run when it is at different torque demands due to the road conditions. The rotational speed is at the highest efficiency ensuring that the internal combustion engine outputs enough torque. The actual power output of the internal combustion engine and the electric motor is obtained by using a defuzzification method, and the data is calculated to output the torque provided by the actual internal combustion engine and the state of charge of each period of the battery pack. In the process of input fuzzy editing, the actual torque output of the internal combustion engine is the main objective, and the state of charge of the motor is limited. The membership function of the input and output is 11.

A greater number will make the calculation more difficult while smaller will make the working range of the internal combustion engine inaccurate and cannot effectively improve the efficiency of the internal combustion engine. When the state of charge of the battery pack is 0, the membership function is 1. When the state of charge of the battery pack is 11, the membership function is 1. The membership function of the internal combustion engine torque divides into two parts. The first part is 1–6. This situation occurs when the output torque of the internal combustion engine is lower than the total torque output by the parallel hybrid electric vehicle. The second part is 6–11. In this case, the output torque of the internal combustion engine is higher than that of the parallel hybrid electric vehicle. The high-efficiency output torque ranges at different engine speeds collected using the original internal combustion engine model. The defuzzified internal combustion engine operating range is used as input for the overall model to derive the fuel consumption and exhaust emissions of the parallel hybrid electric vehicle.

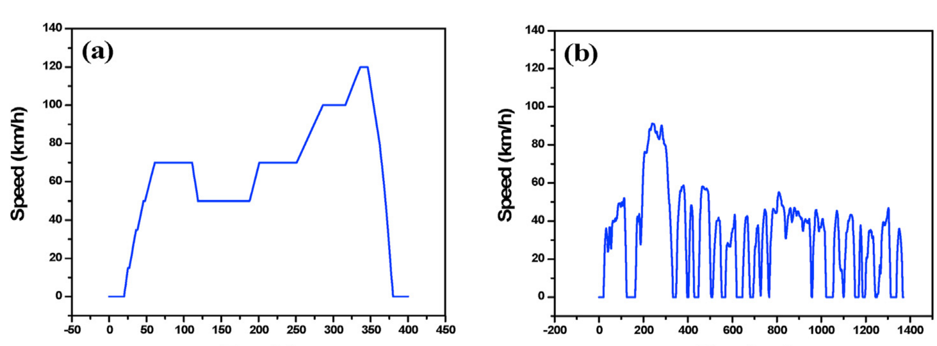

Fig. 5. Speed profile of driving cycles; (a) EUDC and (b) UDDS.

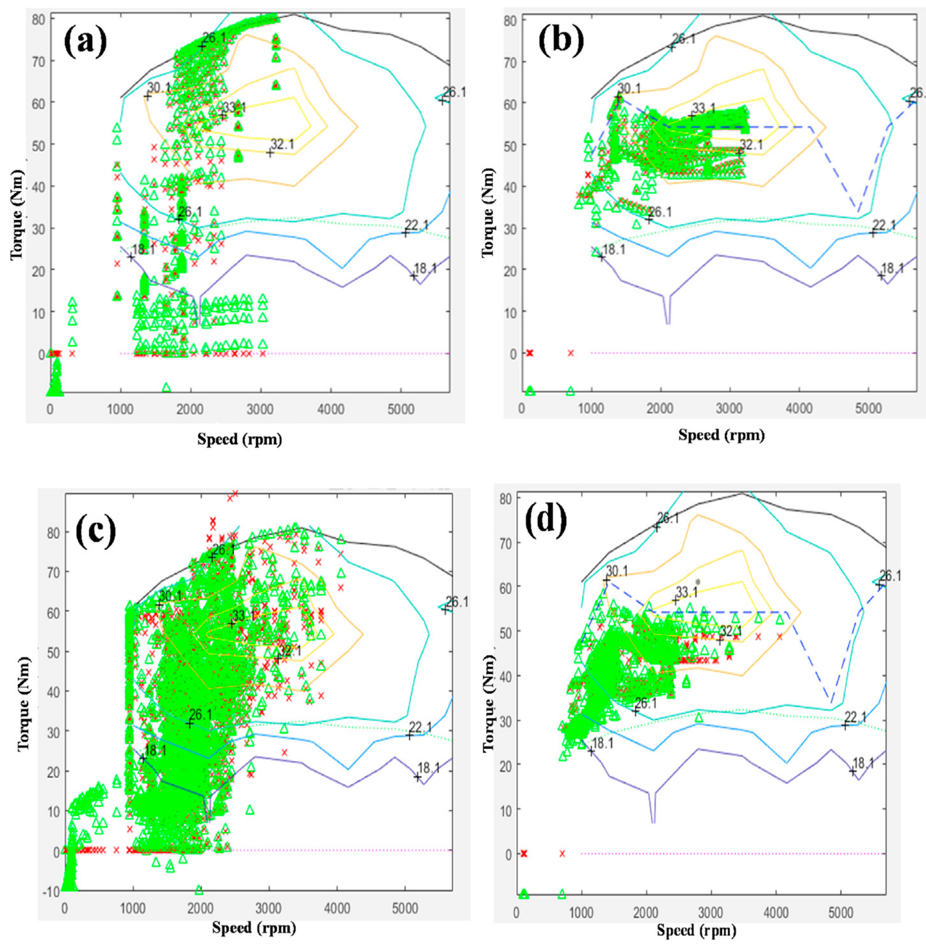

Fig. 6. The internal combustion engine efficiency in EUDC simulated road conditions; (a) before optimization, (b) after optimization and UDDS (c) before optimization and (d) after optimization.

3.3. Effect of road power demand model

The analogue test species are chosen to use two road conditions; Extra Urban Driving Cycle (EUDC) and Urban Dynamometer Driving Schedule (UDDS) that can simulate for different road conditions and are closer to actual road conditions. EUDC is mainly simulated to run on high-speed sections. UDDS primarily operate on urban roads. Four simulations were performed on each segment to prevent data errors. Fig. 5(a) is a road condition display of the simulated driving EUDC. This road condition was used in the study by (Khoucha et al., 2019). The total running time in this road condition is 400 s with a total distance of 6.95 km. Hybrid cars have a top speed of 120 km/h with an average speed of 62.44 km/h. The maximum and average acceleration is 0.83 m/s^2 and 0.38 m/s^2 respectively. Whereas, the maximum and average deceleration is -1.39 m/s^2 and -0.93 m/s^2 respectively. This route has a total of 1 stop section.

The EUDC simulation driving cycle can effectively judge the energy use of the hybrid electric vehicle powertrain under high-speed road conditions. At 25th second, the speed of the vehicle increases from 0 to 70 km/h and remains constant for 50 s. After that, it starts to decline to 50 km/h where it stays constant up to 200th seconds, then starts to accelerate, and again reaches at 70 km/h. After remaining constant for 50 s, the speed continues to fluctuate, until it reaches the maximum point at 120 km/h and eventually falls to zero at 400th second. UDDS is shown in Fig. 5(b) is an actual road condition that is widely used. According to the simulation test of the previous study (Fu et al., 2012) and others, UDDS is also used to simulate driving conditions. The total running time of the road condition is 1369 s with a total distance of 11.99 km. The maximum speed of the hybrid electric vehicle in this path is 91.25 km/h having an average speed of 31.51 km/h. The maximum and average acceleration of the car is 1.48 and 0.5 m/s^2 respectively. Whereas, the maximum and average deceleration of the car is - 1.48 and -0.58 m/s^2 respectively. The hybrid electric vehicle stopped a total of 17 times in the section.

The electric motor provides the first drive pattern to the system. The vehicle starts from the 30th second and reaches 35 km/h at the 35th second. At 38th second, the speed reduces to 25 km/h and it continues to fluctuate until it reaches at the speed of 51 km/h at 100th second. After the 105th second, power supply breaks and the automobile proceeds to the stationary condition at 120th second. The electrical motor also provides the second drive pattern. From the 190th second, the automobile is advanced forward ahead till it reaches 41 km/h at 200th second. The speed is started to reduce at 201th second and stops at 30 km/h at 202nd second and the started to oscillate until it approaches at a maximum speed of 90 km/h at 250th second. The power supply is stopped after the 300th second and speed of the vehicle goes back to zero at the 350th second. Initially, the electric motor gives power solely to the third drive pattern.

The vehicle begins to go ahead at the 355th second only, because of the postponement of acceleration performance of power supplier. At the 357th second, the system chooses to switch the power by stopping the electric motor operation and in its place, utilizing the internal combustion engine to produce power. An oscillation is caused due to the power switch at 357th second. The vehicle continues to oscillate; the internal combustion engine breaks the power supply after the 390th second then vehicle starts to decelerate. Power is provided by the electric motor at the

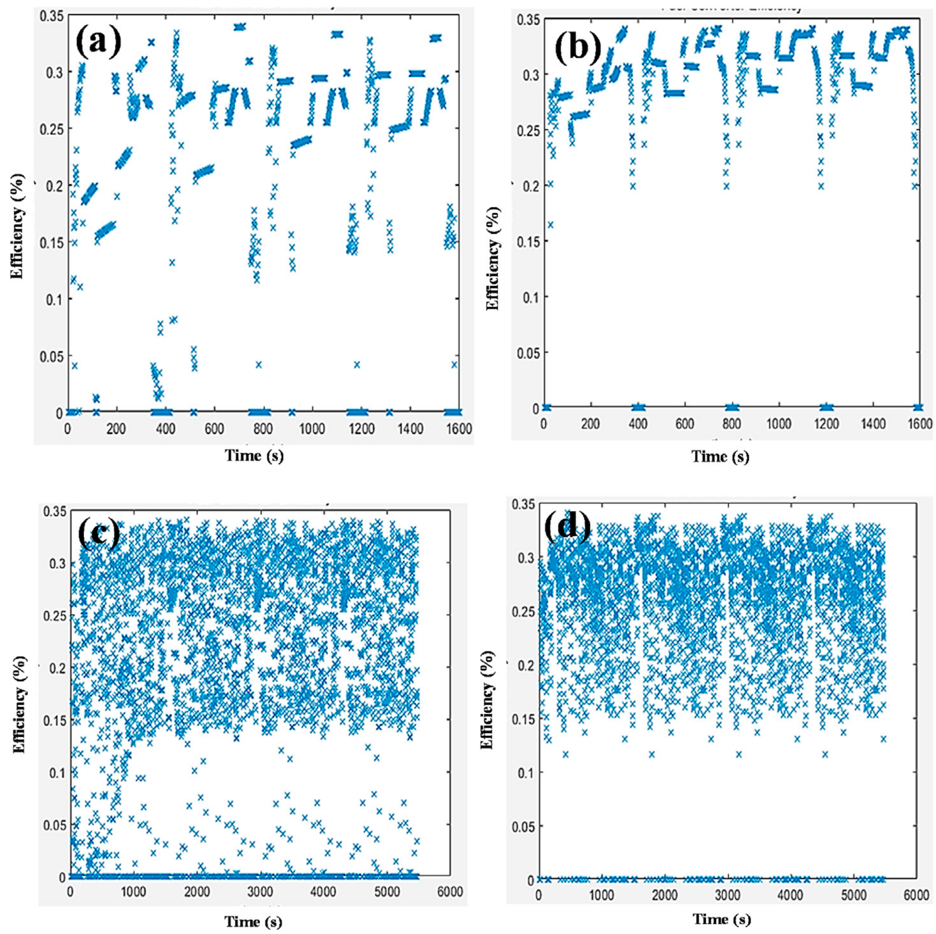

Fig. 7. Fuel converter efficiency in EUDC simulated road conditions; (a) before optimization, (b) after optimization and UDDS, (c) before optimization and (d) after optimization.

395th second and speed of the car begins to decrease from 90 to 30 km/h at 398th second. The power supply is stopped after 400th second and the speed of the car goes back to zero at the 401th second. Electric motor first provides power to the fourth drive pattern at the 410th second and like those in third drive pattern, initial oscillations are generated. The system chooses to switch the power at 415th second by ending the electric motor and to output power, restarts the internal combustion engine. An oscillation rises at the 415th second due to power switch. At the 420th second, the internal combustion engine and electric motor deliver power at the same time and the generator shuts down, due to this power switch another oscillation is produced.

The speed of the vehicle stabilizes at 57 km/h at the 445th second. The output power is stopped by the electric motor at the 448th second and the car begins to slow down until it returns to zero speed at 450th second. Power is provided only by internal combustion engine at the 452nd second and to increase the speed of the vehicle at 40 km/h, the generator is started. The electric motor is started for acceleration and generator shuts down at the 455th second. To fulfil the requirements of the system, the motor surges its power at this second, because to accelerate the vehicle to 50 km/h, speed is needed. Due to this acceleration, a short-term oscillation occurred at 460th second. Similarly, the vehicle returns to zero speed at the time of 590th, 610th, 650th, 700th and 750th seconds and continues to oscillate during these time periods. At the 1310th second, the generator is turned on and the electric motor shuts down. At the 1321th second, the generator and internal combustion engine are turned off. The motor is started at that time and at the 1350th second, the speed is decreased until the motor is shut down. At the 1400th second, the car returns to the stoppage.

3.4. Effect on internal combustion engine efficiency

The green points (in the web version) in Fig. 6(a and b) are the efficiency nodes used by the internal combustion engine at each time node in EUDC simulated road conditions. Before the optimization using fuzzy logic algorithms, the efficiency of the internal combustion engine was much dispersed. Some work nodes were less than 18% efficient. However, after optimization, the internal combustion engine working nodes are concentrated in the dynamic operating range. The operating efficiency range of internal combustion engines has been concentrated in 26.1–33.1% for a long time and these results are comparable with the literature (Sheng et al., 2019) where efficiency is below 30%. Fig. 6(c and d) are distribution diagrams of efficiency of the internal combustion engine before and after optimization in UDDS simulated road conditions.

The working range of the internal combustion engine relatively disperses before the optimization. About half of the time, the efficiency of the internal combustion engine is less than 26.1%. After optimising the internal combustion engine efficiency map, it can be seen that the operating efficiency of the internal combustion engine concentrates between 18.1 and 33.1% for most of the time and these results are more efficient than the work of where efficiency of the engine is 28.70% by using Type 1 Fuzzy Logic Controller and 29.93% by using Interval Type 2 Fuzzy Logic Controller (Phan et al., 2020). Compared with the default engine, the working efficiency of the optimized internal combustion engine has dramatically improved. Fig. 7(a and b) shows the fuel converter efficiency, before and after optimization in EUDC simulated road conditions. When the fuel converter efficiency is zero, it indicates that the internal combustion engine is not involved in the work now that means

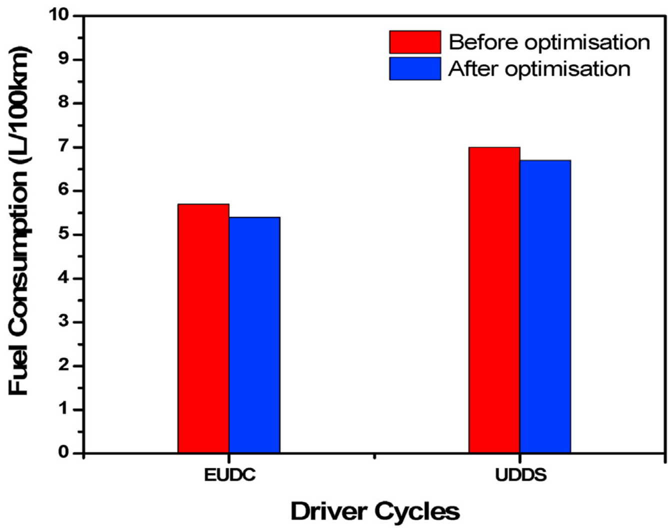

Fig. 8. Comparison of fuel consumption in driver cycles of EUDC and UDDS.

an internal combustion engine is not working at this time.

The distribution of fuel converter efficiency before the optimization is extensive. Nearly one-third of the time nodes have fuel converter efficiency below 15%. The optimized fuel converter efficiency has only one or two, time nodes below 20%. At other times, the fuel converter is more than 20% efficient. Fig. 7(c and d) shows the changes in fuel converter efficiency at different time points before and after optimization in UDDS. Before optimization, the fuel converter had a lower level of efficiency that is 5% for 0–5000 s time nodes. These time nodes are less than 15% efficient. The optimized fuel converter efficiency has dramatically improved after optimization that is 35%. This increase is due to the utilization of UDDS driving cycle. As can be seen from Fig. 7(d), the fuel converter efficiency is higher than 15% for 5000 s time nodes.

3.5. Effect on acceleration performance

The influence of the fuzzy logic algorithm optimization on the engine is not unusually large because it provides the possible ways of optimization that can be adopted by testing. It will not affect the daily driving performance of hybrid electric vehicles. The acceleration time of the 0–100 km/h hybrid electric vehicle is 10 s. The optimized acceleration time of the hybrid vehicle for 0–100 km/h is 10.1 s and it is more efficient than the results of (Peng et al., 2020) where acceleration time is 10.3 s.

3.6. Effect on fuel efficiency and exhaust emissions

Fig. 8 shows the changes in fuel consumption for the Extra Urban Driving Cycle (EUDC) and Urban Dynamometer Driving Schedule (UDDS) before and after optimization. Before optimization, the hybrid electric vehicle had a fuel consumption of 5.7 and 7 L/100 km under EUDC and UDDS conditions whereas it is 5.4 and 6.7 L/100 km respectively after optimization and these results are approximate to the research of (Fu et al., 2019). According to a study (Peng et al., 2020), the fuel economy is less than 5.62 L/100 km under WLTC cycle, also according to the work of (Shi et al., 2020), the fuel consumption is 5.97 L/100 km by using multi neural network (MNN), whereas in the present work under EUDC cycle, fuel economy is 5.4 L/100 km. By comparison, it can be seen that the optimized internal combustion engine has lower fuel consumption under the same road conditions than the original model before optimization. It confirms that the fuzzy logic algorithm can effectively optimize hybrid electric vehicles on high-speed road sections.

Fig. 9(a) is a comparison of exhaust emissions before and after optimization of a hybrid electric vehicle for EUDC. The change in hydroxide and nitrogen oxides was not large before and after optimization. However, carbon monoxide emissions have changed dramatically. Before the optimization, the displacement of carbon monoxide in the hybrid electric vehicle was 1.28 g/km. The optimized carbon monoxide displacement of the hybrid vehicle is 0.63 g/km. These results are comparable with the other studies reported in the literature (Sheng et al., 2019), where carbon monoxide emission is 1.30 g/km after optimization. Fig. 9(b) shows the comparison of exhaust gas emissions data before and after optimization of hybrid electric vehicles for UDDS. The changes in hydroxides and nitrogen oxides are like those in the EUDC road conditions. In the UDDS, the motor intervention time is relatively higher than the EUDC, so the exhaust emissions are relatively low. Carbon monoxide emissions were 0.84 g/km before optimization. After optimization, it is 0.48 g/km. Carbon monoxide is sufficiently reduced in an optimized hybrid electric vehicle.

4. Conclusion

Using the UDDS and EUDC road conditions for simulation, the exhaust gas emissions and fuel consumption of the internal combustion engine before and after optimization were successfully performed. The use of fuzzy logic algorithms to optimize parallel hybrid electric vehicles has achieved significant results. Main research findings are summarised as follows:

- The fuzzy logic algorithm successfully controls the powertrain in an efficient interval. This facilitates the full combustion of the fuel in the internal combustion engine. The operating efficiency of the engine was improved by 15% and fuel converter efficiency by 5%.
- The fuzzy logic algorithm successfully reduces the exhaust emissions of the parallel hybrid vehicle and improves the fuel economy of the vehicle while ensuring that the performance of the vehicle is not affected. If the climbing performance of a vehicle is increased, then

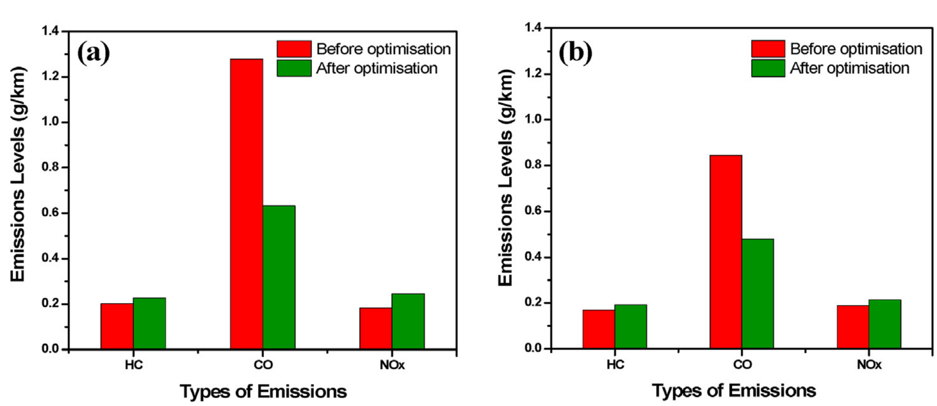

Fig. 9. Comparison of emissions in driver cycles of (a) EUDC and (b) UDDS.

the amount of exhaust emissions also increases, this is due to the large power demand engine will burn more fuel that could be the reason for high emissions, so there is a trade-off between these two factors while selecting a suitable battery pack.

- On the other hand, in order to achieve high acceleration performance, a battery pack with more weight and volume is required, which is not suitable for a vehicle design. This makes the car more competitive in the future.
- In this project, the carbon monoxide emissions of the internal combustion engine were reduced by 50%. Although the carbon monoxide emissions significantly reduced, the contents of nitrogen oxides and hydroxides were not better optimized.
- At the same time, the engine fuel changes before and after optimization are not obvious. This change can only reflect the optimized fuel economy of a hybrid electric vehicle when driving for a long time. In the future work, not only the optimization strategy will be used to improve the efficiency of the powertrain, but also the efficiency of the internal combustion engine, the motor and the battery pack itself.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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