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Design of an Optimal Control Strategy in a Parallel Hybrid Vehicle in Order to Simultaneously Reduce Fuel Consumption and Emissions

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ABSTRACT

In this paper, an optimal control strategy is developed. The control strategy aims to simultaneously reduce fuel consumption and emissions of a parallel hybrid electric vehicle (HEV). A continuously variable transmission (CVT) is implemented in the HEV model. The CVT has a significant role to operate the internal combustion engine (ICE) near its optimal operating points; consequently its proper control will contribute to enhance the fuel economy and emissions. Using a trade-off between the fuel consumption and emission rates, improving the fuel consumption can cause the emission rates to be improved too.

First, 5 different modes for the vehicle motion is defined. Afterwards, depending on the state of charge of the battery (SOC) and the requested power from the driver, the best mode, in each time step, is chosen. Knowing the best mode, the control strategy refers to ICE or electric motor (EM) pre-calculated optimal curves, and determines ICE/EM output speed (i.e. input speed to CVT). The CVT output speed is derived from speed-time diagram of drive cycles. Subsequently, the optimal gear ratio is known. This gear ratio helps the ICE/EM to work optimally, resulting in better fuel consumption and reduced emissions.

The controller tries to maintain the vehicle performance parameters in a defined region. This will assure that driver's power request is fulfilled all the time. The controller tries to use as much regenerative power as possible.

Results of implementing the proposed control strategy are calculated over three different drive cycles. In a part of control strategy, a fuzzy logic controller is used to determine the proper vehicle mode. To achieve better outputs, parameters of the fuzzy controller are optimized using genetic algorithms. Final results showed the optimal control strategy success in reducing fuel consumption and improving or maintaining emissions meanwhile the performance parameters are within the defined limits.

INTRODUCTION

Although use of fossil fuels, especially in terms of transportation, has made a huge progress in human life, nowadays owing to their growing cost as well as their other consequences such as global warming, air pollution, acid rain (i.e. consequences related to emissions released from incomplete combustion of fossil fuels), their usage should be reduced as much as possible.

Several approaches have been suggested such as restricting transportation activity or using alternative energy sources (e.g. fuel cells, wind power, solar energy etc.) [1], but these solutions are not completely practical. It is because, on the one hand, regarding to the increasing number of urbanization, we need more transportation and on the other hand, according to the current technologies and production costs use of alternative energy sources is not completely feasible in large productions.

Increasing the efficiency of current vehicles is another considerable solution. This solution is divided into the following items [2]:

1. Reducing vehicle resistance, i.e. aerodynamic resistance, inertial resistance.

2. Optimizing structure and design of the internal combustion engine (ICE) in order to improve its operational efficiency.

3. Using advanced control methods to match the ICE and transmission more properly.

4. Using new drive trains.

In this paper, the focus is placed on the third item. Hence, a new control strategy is developed to match the transmission and the propulsion system as efficient as possible.

Hybrid electric vehicles (HEVs) use two different sources to propel the vehicle. They are capable of improving fuel economy and air pollution without sacrificing the vehicle performance and drivability. HEVs also have the advantage of using conventional vehicles infrastructure [3]. Series and parallel types are accepted as HEVs basic configurations. These two basic configurations are shown in Fig. 1. In addition to these two well-known configurations, other architectures such as series-parallel (e.g. Toyota Prius [3]) and complex, are also available [4].

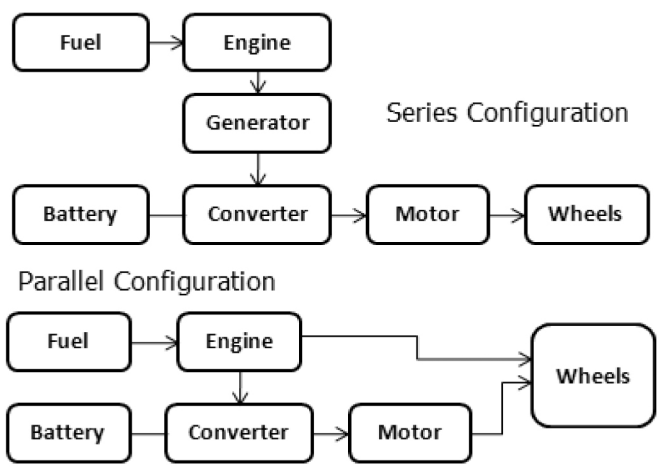


Figure 1. Series and Parallel HEV configurations

In a series HEV, the ICE provides the electrical power to the electric motor (EM) and the EM supplies the mechanical power to the wheels. Hence, in series HEVs the operating speed of the ICE is independent of the wheel speed which helps the engine to work near its maximum efficiency points. However, due to frequent mechanical and electrical energy conversions, the losses are high. Therefore, the total vehicle efficiency is fairly low [5].

On the contrary, in a parallel HEV, the ICE is able to directly supply the mechanical power to the wheels and EM works as a load leveling device. As a result, the engine speed is dependent on the wheel speed and gear ratio. Consequently, although losses pertaining to conversions are less, the vehicle efficiency is low.

In a general comparison, in a parallel HEV a smaller ICE and EM are required to obtain the same performance characteristics as in a series HEV, thus parallel configurations are more convenient for passenger cars whereas series configurations are more suitable for heavy duty vehicles [6]. In this paper, an HEV in its parallel configuration is considered and to overcome the difficulty of losses due to variable engine speed, a continuously variable transmission (CVT) gearbox is employed.

CVTs have an infinite number of gear ratios between their upper and lower limits. Despite having lower efficiency in comparison with a cog wheel gearbox, they are capable of improving total system efficiency [7] (by exact control of gear shifting). This has been done traditionally by identifying the most efficient points in the ICE map and attempting to operate the engine in the vicinity of these points.

Improving the control strategy design is one of the key features in reducing fuel consumption and emissions of an HEV. The control strategy is an algorithm, whereby energy is produced, saved and used [8]. Several approaches have been suggested to control HEVs. One approach emphasizes on optimizing the ICE and remains other major components unchanged; another approach optimizes the instantaneous operation of hybrid system; while the other one targets the global optimization of total fuel consumption or emissions (mostly carbon monoxide, unburned hydrocarbons and nitrogen oxides) over a specific drive cycle [9].

Success of implementing fuzzy logic method in design of control strategies in HEVs has been demonstrated in a lot of works ([6], [9,10,11,12]). Fuzzy logic is a suitable method for decision-making problems; it also applies well to nonlinear systems with time-varying parameters. Hence, in a part of proposed control strategy, a fuzzy logic controller is used as a sub-controller to determine the proper vehicle mode.

Some of the mentioned works try to optimize the control strategy by means of optimizing the ICE operation ([8]) while others try to optimize more than one major component ([5,11]).

In order to reach a more realistic evaluation of the fuel economy and emissions, three commonly used drive cycles (American FTP, European NEDC and Japanese 1015) were used. These drive cycles were chosen from three different area to investigate the effectiveness of implementing the optimal control strategy more generally. The specifications of drive cycles are summarized in Table 1. Figure 2 shows the diagram of selected drive cycles.

Table 1. Characteristics of drive cycles

Drive cycle	FTP	NEDC	1015 Japan
Time (s)	2477	1184	660
Distance (km)	17.77	10.93	4.16
Max. speed (km/h)	91.25	120	69.97
Avg. speed (km/h)	25.82	33.21	22.68
Max. acceleration (m/s^2)	1.48	1.06	0.79
Max. deceleration (m/s^2)	-1.48	-1.39	-0.83
Avg. acceleration (m/s^2)	0.51	0.54	0.57
Avg. deceleration (m/s^2)	-0.58	-0.79	-0.65
Idle time (s)	361	298	215
No. of stops	22	13	7

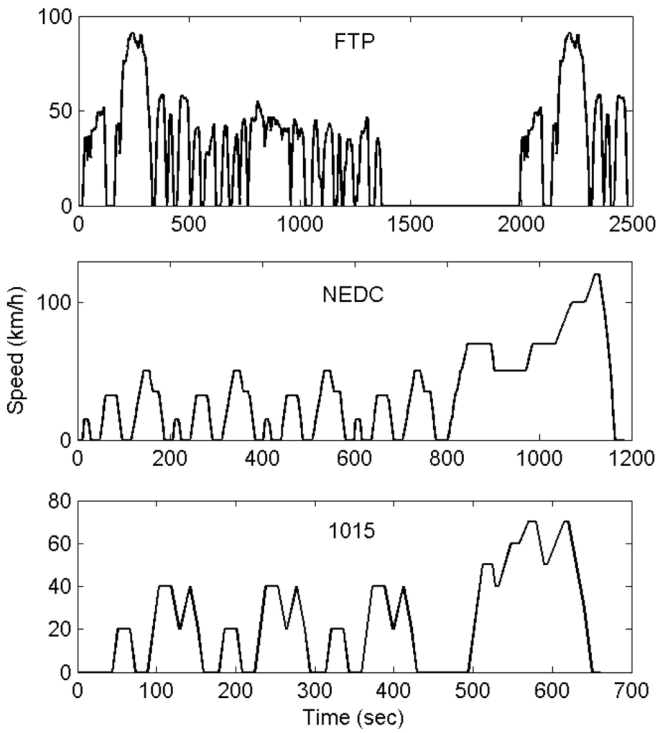


Figure 2. Speed-time diagram of selected drive cycles

Knowing the proper mode in each time step, the controller refers to the pre-calculated ICE or EM optimal curves. Subsequently, with regard to the requested power, the controller determines the ICE/EM optimal operating speed (i.e. input speed to the CVT). The CVT output speed is derived from the drive cycle diagrams. The relevant gear ratio is calculated by dividing the input speed to the output speed. This gear ratio helps the ICE/EM to work optimally, resulting in better fuel consumption and reduced emissions.

CONTROL STRATEGY DESIGN

OPTIMAL CURVES

Here the control strategy objectives are set from the fundamental to the desired vehicle requirements. The control strategy must:

1. Sustain the final state of charge of the battery (SOC) at the end of drive cycle in a vicinity of its initial state.

2. Maintain or enhance the vehicle performance characteristics. Partnership for New Generation Vehicles (PNGV) constraints [13] are used to ensure that the driver's request is always fulfilled regardless of the control strategy manipulations. The PNGV constraints are listed in Table 2. It should be noted that the PNGV criteria is originally applied to a family car seating 5 individuals while it satisfies 80 miles per gallon (2.94 L/100km) gasoline fuel economy on U.S. fuel economy drive cycles. However, this paper only considers the PNGV performance requirements and tries to reduce fuel consumption by improving the control strategy.

3. Improve the fuel economy on the condition that emission rates do not exceed the restrictions. These restrictions could be defined based on the environmental contracts (e.g. Euro standards) or designer goals.

Table 2. The PNGV constraints for minimum vehicle performance requirements [13]

0–97 km/h	≤ 12 s
0–137 km/h	≤ 23 s
64–97 km/h	≤ 5.3 s
Distance in 5 s	≥ 42.7 m
Maximum acceleration	≥ 5.2 m/s2
Max. road grade at 89 km/h with 272 kg added mass, for 20 min	≥ 6.5%
Maximum speed	≥ 161 km/h

Figure 3 shows the loci of operating points for an example of an ICE [14], implying that the fuel consumption reduction does not always lead to reduced emissions.

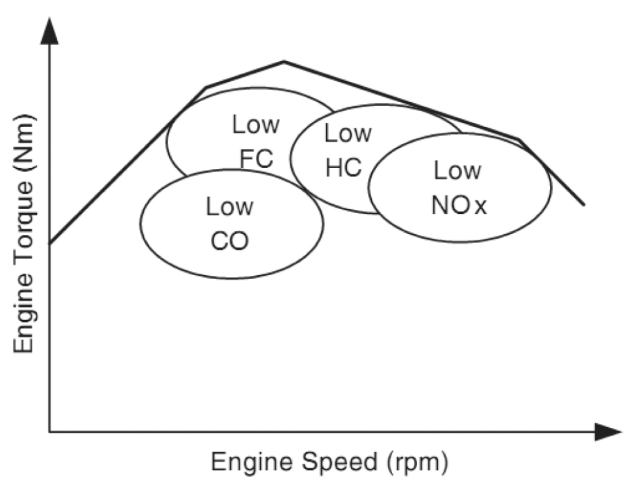


Figure 3. An example of the optimal operating points for an ICE [14]

Therefore, there should be a trade-off between reducing fuel consumption and reducing emissions. The following cost function is defined to achieve the optimal curve satisfying the third objective:

$$Cost\ Fcn = \frac{1}{w_1+w_2+w_3+w_4}\left(w_1\frac{FC}{\overline{FC}} + w_2\frac{HC}{\overline{HC}} + w_3\frac{CO}{\overline{CO}} + w_4\frac{NO_x}{\overline{NO_x}}\right) \quad (1)$$

Where FC, HC, CO and NO_x stand for the fuel consumption, unburned hydrocarbons, carbon monoxides and nitrogen oxides, respectively. $\overline{FC}$, $\overline{HC}$, $\overline{CO}$ and $\overline{NO_x}$ are target values used to normalize each variable and w_i (i=1:4) is the weighting factor. Using FC, HC, CO and NO_x maps, the cost function for all possible torques in the speed range of engine is calculated. The outcome curves (named cost function map here) are shown in Fig.4. In the current study, for the target values in Eq. (1), the mean value in each concerning map (i.e. FC, HC, CO and NO_x maps) is used. The weighting factor for FC is set to 2 and emissions weighting factors are set to 1.

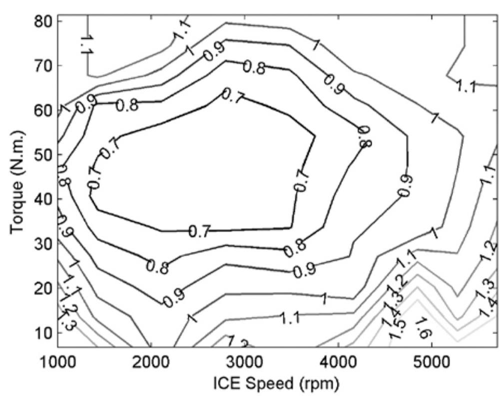


Figure 4. Calculated cost function map

In each specific speed the torque corresponding to the least cost function value is considered as the optimal torque. The ICE maximum torque and the achieved optimal torque curves (applying the cost function) are depicted in Fig. 5.

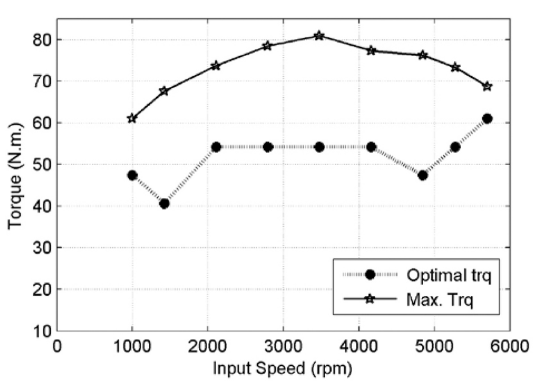


Figure 5. Maximum and achieved optimal torque curves for the ICE

For the EM the optimal curve is plotted based on having the highest efficiency in each specific speed. The maximum and obtained optimal curves are shown in Fig. 6. At any specific speed, the output power is calculated by multiplying the torque and the corresponding speed.

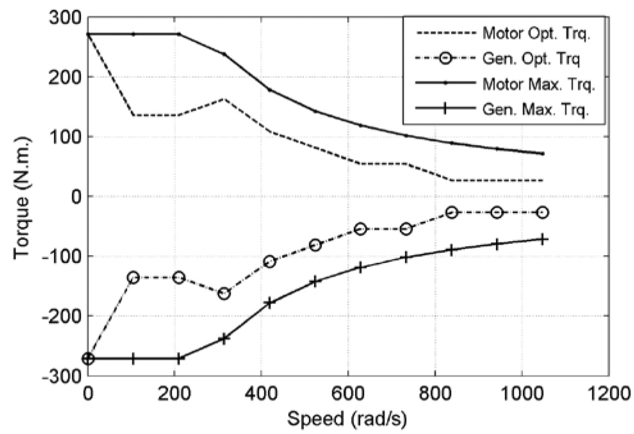


Figure 6. Maximum and optimal operating points for the EM/generator

OPTIMAL GEAR RATIO

The control strategy aims to choose the best gear ratio to satisfy the objectives discussed in the previous section. The vehicle motion is divided into 5 different modes:

1. reducing speed (i.e. regenerative braking mode)
2. propelling with the EM (i.e. ICE is switched off)
3. propelling with the ICE (i.e. EM is switched off)
4. propelling with both ICE and EM together
5. propelling with the ICE and charging the batteries with EM (working as a generator)

In the last mode, the ICE produces the propelling power just by itself and the EM (i.e. generator) works only to charge the battery thus in the control strategy this mode is considered as a part of mode 3.

Observing the vehicle condition, like the SOC and road demands (i.e. power requested to pass the drive cycle), the controller determines the proper mode. Afterwards, referring to the optimal curves (i.e. figures 5 and 6) the corresponding speed of the ICE/EM is obtained; this is the CVT input speed whereas CVT output speed is derived with regard to speed-time diagram of the drive cycles and drive train configurations. Consequently, the concerning gear ratio is obtained from Eq. (2):

$$Gear\ Ratio = \frac{Input\ \ Speed}{Output\ \ Speed} \tag{2}$$

The flowchart of choosing CVT gear ratio is summarized in Fig. 7. The gear ratio is chosen based on the SOC and the driver's requested power. The driver's requested power is equivalent to the power required to pass the drive cycle.

If the requested power is positive, the control strategy will compare it with the optimal and maximum ICE powers at the specified speed. Result of this comparison belongs to one of these categories:

1. The requested power is negative. Therefore, the controller chooses mode 1. Although the control strategy tries to regenerate as much braking power as possible, only 60% of the braking power is regenerated and the rest is provided by friction brakes. It is because in the current vehicle model only front wheels are capable of regenerating.

2. The requested power is more than the ICE maximum power. The controller chooses mode 4 and the EM assists the ICE to propel the vehicle.

3. In spite of being positive, the requested power is less than the ICE maximum power. In this category two modes are possible: mode 2 or mode 3. Here a fuzzy controller determines the proper mode. In mode 3, the controller calculates the engine excess power to charge the battery as well.

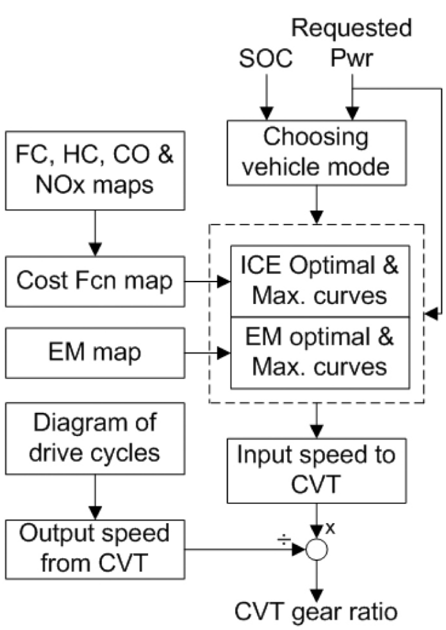


Figure 7. Flowchart of choosing CVT optimal gear ratio

FUZZY CONTROLLER DESIGN

Design of a fuzzy controller consists of two main steps: design of structure and design of parameters. The structure of the applied fuzzy controller is listed in Table 3. The requested power and the SOC are the fuzzy controller input variables while the output variable is the ICE output power.

Table 3. Structure of the applied fuzzy controller

Fuzzy system Type	Mamdani [15]
AND operator	Minimum
OR operator	Maximum
Implication method	Minimum
Aggregation method	Maximum
Defuzzification method	Centroid

Each variable has three membership functions (MFs), resulting in nine rules. Figure 8 shows the MFs for input variables.

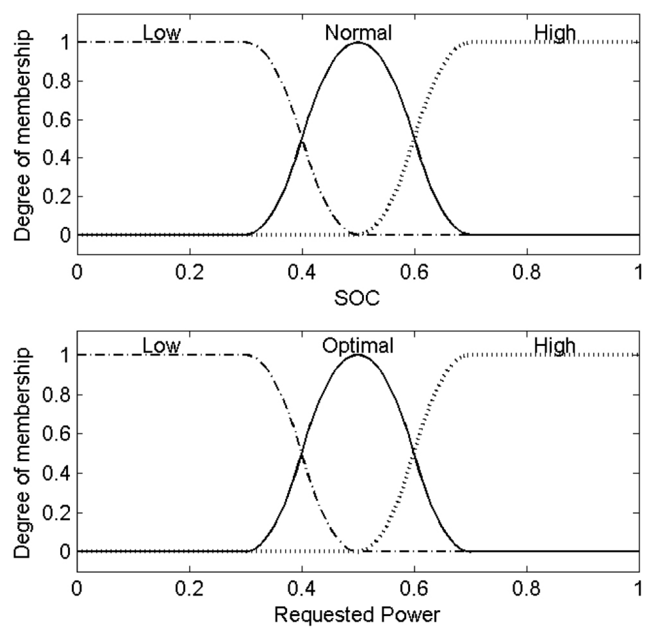


Figure 8. Initial MFs for the SOC and requested power

Output MFs are the same as requested power MFs, inasmuch as these MFs are both for the same engine i.e. they are based on the same characteristics [8]. The fuzzy rules are listed in Table 4. These rules are based on designer intuition of the problem.

Table 4. Fuzzy rules used to determine the ICE output power

	If SOC is:	and requested power is:	then ICE output power is:
1	Low	Low	*Optimal*
2	Normal	Low	*Low*
3	High	Low	*Low*
4	Low	Optimal	*High*
5	Normal	Optimal	*Optimal*
6	High	Optimal	*Optimal*
7	Low	High	*High*
8	Normal	High	*High*
9	High	High	*Optimal*

Using optimal and maximum powers at any specified speed, the input power is normalized between 0.0 and 1.0. After normalization, in each time step, 0.0 indicates zero engine power, 0.5 indicates the optimal power and 1 indicates the maximum power.

The SOC is normalized, too. The highest and the lowest limits of SOC are usually determined by means of the battery charge and discharge resistance curves. These curves are shown in Fig. 9. With respect to these curves, SOC of 0.6 is selected as the target point which the battery is very close to its lowest charge and discharge resistances. The highest and the lowest SOC limits are chosen as close as possible to this target value. In this paper SOC of 0.5 is selected as the lowest SOC and 0.7 is selected as the highest SOC. Thus, 0.0 represents the lowest SOC, 0.5 represents the target value and 1.0 represents the highest SOC. In the current battery model, these two curves have overlapped.

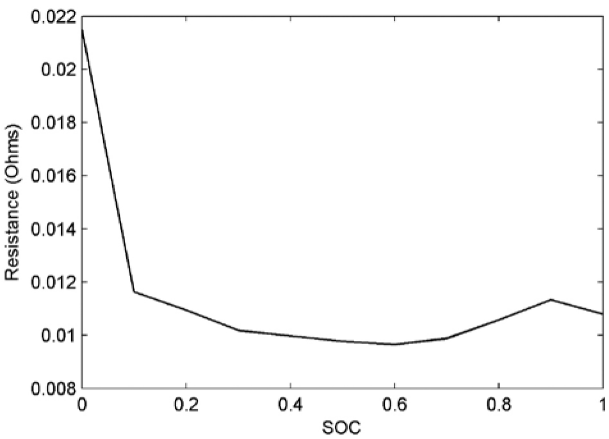


Figure 9. Charge and discharge curves of the battery (overlapped)

According to Table 4, if the output power is "low" (e.g. less than 5 kW), the fuzzy controller concludes that the SOC was in "normal" or "high" region and the EM can sufficiently provide the propelling power, hence the fuzzy controller will choose mode 2. If the output power is not low, the fuzzy controller will choose mode 3 and the ICE excess power is calculated regarding to Eq. (3):

$$Excess\ power = ICE\ output\ power - requested\ power \quad (3)$$

OPTIMIZING the FUZZY CONTROLLER

Designed fuzzy controller does not necessarily return the best results. In this section in order to obtain optimal outputs, MFs of the fuzzy controller are optimized using multi-objective optimization Genetic Algorithms. Optimization with the genetic algorithms can be summarized into 5 main steps [16]:

1. Generating the initial population

2. Evaluating each member using a fitness function (if the criteria is fulfilled the process ends)

3. Selection of qualified members and generating a new population

4. Application of genetic operators (crossover, mutation)

5. Returning to the second step

Although in a total optimization, structure and parameters of the fuzzy controller should be optimized, here with regard to the simplicity of the designed fuzzy controller (including 2 inputs, 3 MFs for each input and a total of 9 fuzzy rules) and its role in the control strategy, the fuzzy controller structure is fixed and only parameters are optimized. In addition, fuzzy rules were developed based on expert knowledge about the problem (with trial and error); therefore, they can stay unchanged.

The position of variable and fixed points in MFs is depicted in Fig. 10. In optimization process position of each marked point (i.e. points A_1 to A_4, in input and output MFs) varies which results in producing new MFs. Using new MFs, each drive cycle is simulated iteratively and outputs are obtained and saved. These simulation results serve as the initial population for the genetic algorithms. In Fig. 10, position of two mid-points (C_1 and C_2) is fixed at 0.5 and position of A_1 and A_2 change from 0.0 to 0.5 whereas A_3 and A_4 change from 0.5 to 1.0.

Normalizing the input variables, fixing the positions of C_1 and C_2 and restricting the change range of A_1 to A_4 points help to keep the linguistic labels of the fuzzy rules (i.e. low, normal etc.) unchanged. Hence, fuzzy rules are considered to be fixed and only the MFs are optimized.

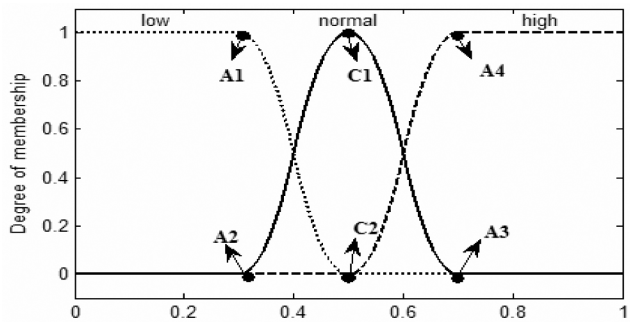


Figure 10. The position of variable and fixed points in MFs of SOC (and Requested power)

ARTIFICIAL NEURAL NETWORK

Simulating all possible new MFs takes a lot of time, thus for each varying point just two positions are considered. Then, based on these simulation outputs (8 points, each having 2 different positions which will result in 2^8=256 simulation for each independent drive cycle) a forward-facing artificial neural network is chosen to train the input data.

It should be noted that using the same hardware, simulating each drive cycle takes more than 30 minutes while applying the neural network reduces the simulation time to less than 3 minutes, depending on the drive cycle.

The neural network has three hidden layers. The number of neurons for the hidden layers is 20, 15 and 4. For neural network design, position of eight varying points in input MFs (i.e. 4 points in the SOC and 4 points in the requested power MFs) are considered as neural network inputs and four ICE outputs (i.e. the rates of FC, HC, CO, and NO_x) are considered as neural network outputs. A tansigmoid function is used as the transfer function of the hidden layer neurons. The neural network is trained with conventional Back-Propagation algorithm.

RESULTS

The advanced vehicle simulator Advisor [17] is used for simulation studies. Specifications of the major components of the parallel HEV model are listed in Table 5. The size of components is chosen to achieve the PNGV constraints listed in Table 2.

The initial SOC is set to 0.6 and to satisfy the charge sustaining requirement, each simulation is repeated (i.e. using an iterative algorithm) until the difference between the final and the initial SOC is less than 0.5% of its initial SOC. Figure 11 shows the history of SOC over NEDC drive cycle. This figure indicates that the charge sustaining constraint is fully satisfied; furthermore, it shows that the control strategy forces the SOC to be very close to its initial value, helping to increase the battery life time.

Table 5. Specifications of major components of the parallel HEV

ICE characteristics	
Type	Geo Metro, SI Engine
Engine volume	1.0 Liter
Maximum power	41 kW at 5700 rpm
Peak torque	81 N.m. at 3477 rpm
Peak efficiency	0.34
EM characteristics	
Type	Westinghouse AC induction motor/inverter
Maximum power	75 kW
Maximum speed	10000 rpm
Peak efficiency	0.92
Battery characteristics	
Type	Ovonic NiMH HEV battery
Number of modules	25
Nominal capacity	45 Ah
Nominal Voltage	12 V
Transmission	
Type	Hydromechanical CVT with
	integrated differential
Gear ratios	continuum of gear ratios from 3 to 15
Efficiency	It differs with speed, torque and gear ratio from 0.7091 to 0.9256
Vehicle characteristics	
Wheel radius	0.282 m
Rolling resistance	0.0009
Vehicle front area	2.0 m^2
Aerodynamic drag coef.	0.335
cargo mass	136 kg
Total mass	1271 kg
Torque coupling	Lossless belt drive
Catalyst converter	Close-coupled conventional catalyst

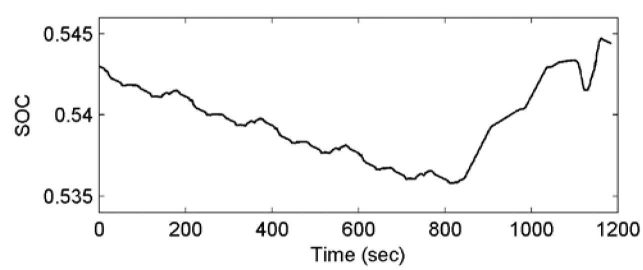


Figure 11. History of SOC over NEDC drive cycle

Figure 12 depicts the optimized MFs of the SOC for FTP and NEDC drive cycles. This figure demonstrates that the optimal MFs are dependent on the drive cycle, implying that an optimized fuzzy controller for a specific drive cycle does not necessarily apply to other drive cycles. Optimized MFs for requested power are shown in Fig. 13.

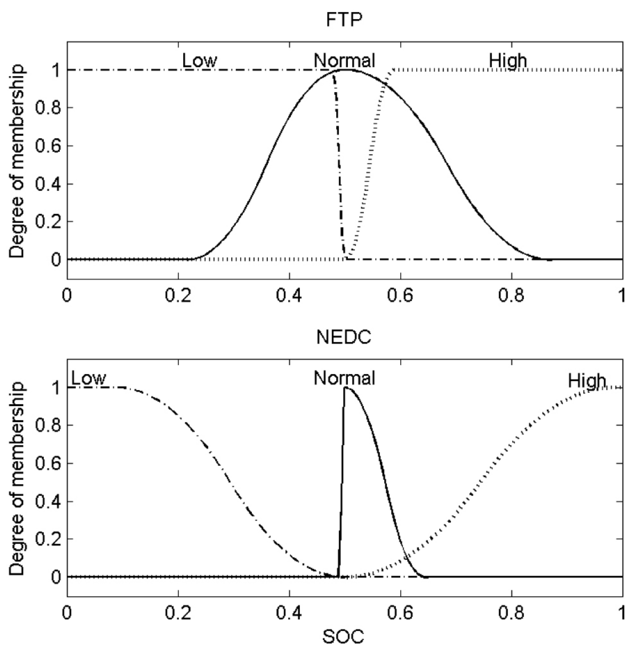


Figure 12. The optimized MFs of the SOC for FTP and NEDC drive cycles

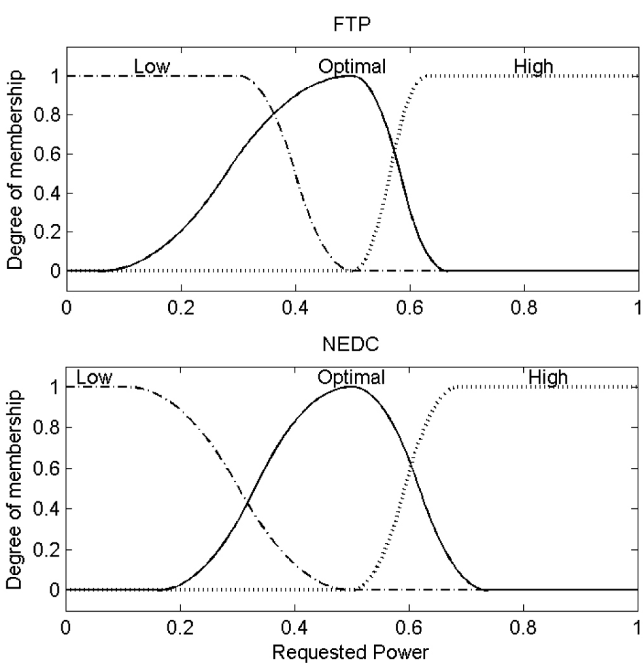


Figure 13. The optimized MFs of the requested power for FTP and NEDC drive cycles

The performance parameters of the parallel HEV are summarized in Table 6. This Table reveals the success of the optimized control strategy in achieving the PNGV constraints.

Results of implementing optimized control strategy versus initial control strategy are summarized in Table 7. It should be noted that this table shows post catalyst emissions. In addition, results of implementing Advisor default controller in the parallel HEV model are given in Table 7.

Table 6. Performance characteristics of the modeled vehicle

0–97 km/h	8.1 (s)
0–137 km/h	16.4 (s)
64–97 km/h	3.9 (s)
Distance in 5 s	57.8 (m)
Maximum acceleration	5 (m/s)
Max. road grade at 89 km/h with 272 kg added mass, for 20 min	7.3 %
Maximum speed	200.5 (km/h)

Table 7. Results of implementing initial, optimized and Advisor controllers (FC is in L/100km, emissions are in g/km)

Drive cycle	Controller Type	FC	HC	CO	NO_x
FTP	Advisor	6.68	0.29	1.20	0.32
	Initial	6.40	0.30	1.19	0.33
	Optimized	6.25	0.30	1.15	0.32
NEDC	Advisor	6.88	0.43	1.32	0.38
	Initial	6.51	0.44	1.46	0.42
	Optimized	6.43	0.42	1.39	0.36
1015	Advisor	7.58	0.97	2.70	0.74
	Initial	6.94	0.99	3.20	0.85
	Optimized	6.87	0.99	3.21	0.84

It is seen from Table 7 that in comparison between initial and optimized outputs, in all the cases (except for CO in 1015 drive cycle) the emission rates have reduced which verifies the success of proposed optimization method. The increase in the amount of CO in 1015 cycle is a result of optimization method used. The output of multi-objective optimization is a set which is an optimal trade-off between all the variables but is not necessarily optimal for all of them individually. Hence, it is possible to have sets with very favorable fuel consumption but with drastically increased emissions. To compensate this, a constraint is added to the optimization problem which does not allow the values of optimized emissions to be 1% more than the initial values (results of the initial fuzzy controller). Data of Table 7 verify that this constraint has worked properly.

On the other hand, comparison between ADVISOR default controller and optimized control strategy shows that the fuel consumption in all the three drive cycles has reduced while the rates of some emissions have increased (HC in FTP, CO in NEDC, HC, CO and NO_x in 1015). It is because the ICE optimal curve (Fig. 5) was derived based on a trade-off between fuel consumption and emissions, so it is optimal for all the parameters altogether but not necessarily for each one of them at the same time.

The control strategy goal was to reduce fuel consumption and emission rates as much as possible; so the weighing factors in cost function (Eq. (1)) were set to 2, 1, 1 and 1, respectively. However, varying these weighting factors will change the ICE optimal curve and hence different optimal MFs will be expected. For instance, when the FC weighing factor is set to 1 and the emissions weighting factors are all set to 0, the controller will only focus on reducing the fuel consumption, regardless of emissions (this case is called FC-targeted problem here).

These new weighting factors (w_1=1, w_2=0, w_3=0, w_4=0) are implemented in the cost function and the new optimal curve is calculated. This curve is depicted in Fig. 14. Figure 15 shows the optimal MFs for FC-targeted problem over FTP drive cycle.

Comparing figures 12, 13 and 15 supports the theory that varying weighting factors in cost function changes the optimal MFs; resulting in different outputs. Comparison of FC-targeted and trade-off results is summarized in Table 8.

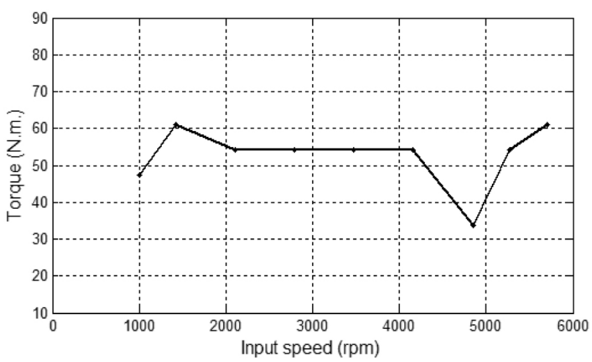
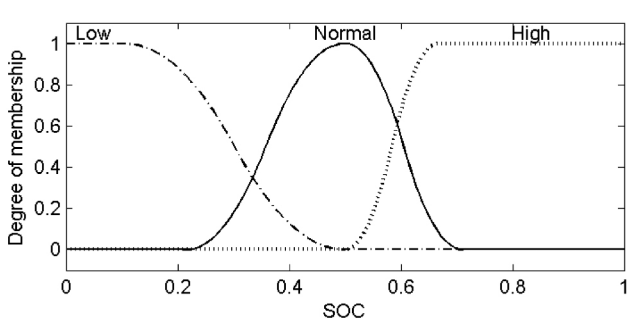


Figure 14. ICE optimal curve for FC-targeted problem



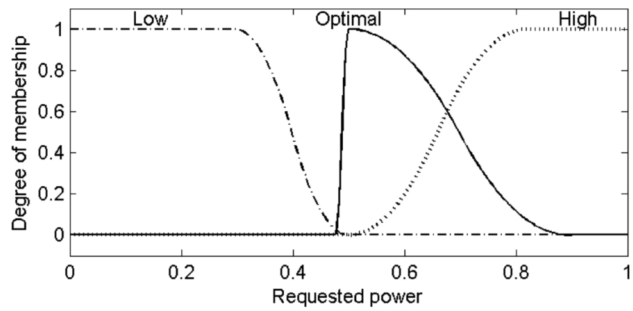


Figure 15. Optimal MFs for FC-targeted problem over FTP drive cycle

Table 8. comparison of FC-targeted and trade-off results over FTP cycle (FC is in L/100km, emissions are in g/km)

	FC	HC	CO	NO_x
Trade-off	6.246	0.297	1.151	0.323
FC-targeted	6.222	0.300	1.152	0.324

It is seen from Table 8 that although the consumed fuel in FC-targeted optimization is less, the rates of produced emissions are higher than those for the trade-off problem.

CONCLUSIONS

In this paper, an optimal control strategy was developed. Designing the control strategy based on finding the CVT best gear ratio, is the underlying theme of this work.

In order to obtain more reasonable results, the initial controller parameters were optimized using multi-objective genetic algorithms and to reduce simulation time an artificial neural network was trained. The neural network reduces the calculation time by more than 90%.

Results show that the optimized controller is capable of improving the fuel economy by about 2% over the initial controller and about 6.5% over the Advisor default controller. This implies the effectiveness of proposed control strategy and the optimization method used, in reducing fuel consumption and emissions (whenever possible) in the parallel HEV.

The powers demanded to produce the accelerations required to pass the drive cycles are less than those required to fulfill the PNGV constraints. Therefore, if the vehicle is able to satisfy the PNGV constraints, it will satisfy the requirements for tracking the drive cycle. This ensures that the driver demand is always fulfilled.

Another feature of the controller is that it adequately charges the battery all the time. This feature facilitates the use of the

EM in high power demanding situations and helps to prolong the battery life time.

One of the reasons for choosing fuzzy logic for the controller design is its robustness to systems with variations. The future work can include the investigation on the robustness of the developed fuzzy controller.

It is shown that drive cycles affect the shape of optimized MFs. Thus, as an additional work, an adaptation algorithm could be added to the proposed control strategy to recognize the current road situation and adapt the fuzzy controller parameters to work optimally with the current driving situation.

To enhance the vehicle overall efficiency, it is essential to optimize not only the control strategy but also the component sizes of hybrid vehicle. So, to improve fuel economy and emissions of the parallel HEV more effectively, optimization of the component sizes should be considered, as well.

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ABBREVIATIONS

CO
Carbon monoxide

CVT
Continuously Variable Transmission

EM
Electric Motor

FC
Fuel Consumption

FTP
Federal test procedure

HC
Unburned hydrocarbon

HEV
Hybrid electric vehicle

ICE
Internal combustion engine

MFs
Membership functions

NEDC
New European drive cycle

NO_x
Nitrogen oxides

PNGV
Partnership for new generation vehicle

SOC
State of charge of the battery

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