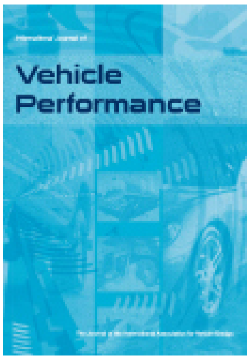

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Performance investigation and energy optimisation in hybrid electric vehicle model using reinforcement learning and fuzzy controller

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Abstract: Hybrid electric vehicles (HEVs) are considered as one of the prominent solutions in reducing vehicular emission. Batteries and internal combustion engines (ICE) are the important components of a HEV, which acts as primary and secondary power source respectively. They simplify the refuelling process by minimising fuel consumption and by reducing virulent emissions. In this research, a series-parallel drivetrain – HEV model is proposed for investigating the performance and energy optimisation of the HEVs. The model is trained to operate at near optimum efficiency for minimising the energy loss. A deep reinforcement learning and fuzzy logic controller based energy management approach is proposed to optimise the energy consumption in HEVs. Results show that the energy management system (EMS) of the model is controlled effectively by the deep reinforcement learning (DRL) algorithm. Effective speed control is achieved by fine tuning the parameters using a fuzzy based PID controller which can be validated from the simulation results.

Keywords: HEVs; hybrid electric vehicles; series-parallel drivetrain; EMSs; energy management systems; DRL; deep reinforcement learning; fuzzy control logic; PID controllers; speed control.

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1 Introduction

Hybrid electric vehicles (HEVs) are regarded as an optimistic substitute for conventional fuel based vehicles, because of their effectiveness in reducing vehicular pollution and noise. The batteries and internal combustion engine (ICE) in HEV's play an important role in reducing vehicular emission thereby contributing towards a pollution free ecosystem. Battery is one of the significant components in HEV's, whose performance is evaluated with respect to different circuit parameters such as open circuit voltage (OCV), state of charge (SOC), battery resistance and power capacity. These parameters are highly sensitive towards temperature, battery ageing and charging/discharging cycle of the battery (Panday and Bansal, 2015). In HEV's, the battery and ICE act as primary and secondary power sources respectively. They both increase the driving range of the vehicle and ease the mechanism of refuelling with minimised fuel consumption and reduced virulent emissions. HEVs store the electrical power in batteries which significantly reduces the energy demand. In this way, HEVs reduce energy requirement by replacing fossil fuel consumption with electrical energy consumption (Panday et al., 2016). The energy management unit in HEV's uses a rechargeable energy storage system (RESS) which acts as an energy buffer and can be employed for regenerative braking. RESS stores the additional energy which is not required by the system at that particular point of time. For example, in most of the times, the power delivered by ICE is different from the power required by the load and in such cases, RESS provides the flexibility of utilising only the required amount of power while utilising the unused power for charging the battery (Onori et al., 2016). RESS in HEV's offers the feasibility of operating the engine in favourable conditions where there is less emissions. Also, there is a possibility of terminating the engine operation when it is not required (i.e., during low speed conditions) and the engine can be downsized by storing the peak power using RESS (Sun et al., 2015). Though HEV's are efficient in reducing fuel consumption, they suffer from certain drawbacks such as low density and low efficiency. Also the cost of the refuelling infrastructure is quite high, which makes it expensive for small scale applications (Sulaiman et al., 2018). Most of the researchers have focussed on developing an efficient energy management system (EMS) for overcoming the limitations of the conventional HEV's. Advanced EMS models include energy minimisation techniques and application of machine learning and deep learning approaches for increasing the flexibility of the EMS. These approaches are gaining prominence because of their reduced computational complexities and no requirement of pre-defined knowledge (Zhou et al., 2019). There are three main categories for EMS which are rule based EMS, optimisation based EMS and learning based EMS. Rule based EMS are mainly dependent on the outcome of the detailed experimental analysis without having the preliminary knowledge about the conditions of driving. Fuzzy based rules are applied for controlling these EMSs. Optimisation based EMS are used when the control strategies of the HEVs are anticipated on subsequent driving scenarios like dynamic programming (DP) (Ansarey et al., 2014; Vagg et al., 2016), sequential quadratic programming (SQP), genetic algorithms (GA) (Chen et al., 2014), the Pontryagin least guideline (PMP) (Xie et al., 2017). These rules decide the desired power split between the engine and the motor for a specific driving cycle. Learning – based EMS learn from the predefined information or utilise the past driving information for web based learning or application (Tian et al., 2018). Various simulation models have been proposed for HEV's based on the prerequisites of the systems. Such as series HEVs, parallel HEV's and series parallel HEVs (Meradji et al., 2016).

In this research, the HEV model is developed using a series parallel drivetrain with reinforcement learning and fuzzy logic controllers for investigating the performance and energy optimisation of the HEVs.

The main contributions of this paper can be summarised as follows:

- This paper presents a novel deep reinforcement learning-based framework for energy management in a series parallel drivetrain-HEV model.
- A DRL based deep Q-learning algorithm is employed for achieving energy optimisation in the HEV
- A fuzzy based PI controller is designed for tuning the system parameters.
- The performance of the HEV model in terms of key equations, parameters, and assumptions.

The rest of the paper is structured as follows: Section 2 discusses the review of existing literary works related to energy management in electric vehicles. Section 3 provides a brief description of the proposed methodology for energy management which includes the design of HEV, control of series-parallel drivetrain and implementation of fuzzy logic controllers. Section 4 discusses the simulation results and Section 5 concludes the paper with prominent research observations and future scope.

2 Literature review

Tang et al. (2017) Proposes a novel approach of a simplified torsional vibration dynamic model for analysing the functionalities of the torsional vibration of a compound planetary hybrid propulsion model. The study evaluates the prominent characteristics such as frequency and vibration property. This model can be employed for determining the low-frequency vibrational attributes of the series parallel drivetrain. It also evaluates the controlling mechanism of the hybrid powertrain with respect to engine operation. Wang et al. (2015) analysed a four wheel driven series parallel drivetrain model for heavy duty applications. The model incorporates a rule-based EMS and the performance of the model was evaluated by comparing the model with a rear-wheel-driven hybrid powertrain and the operational parameters are optimised. The proposed model was integrated with a transit bus and the functionalities of the bus were evaluated. Unlike conventional coaxial power-split HEV's, the energy consumption was minimised using the series parallel drivetrain when evaluated for normal road conditions. SPHEV has great potential in minimising energy consumption. However, due to certain uncertainties such as multi power resources and varying driving constraints, it is challenging to develop an optimal EMS. Wang et al. (2018) proposed a novel particle swarm optimisation (PSO) based nonlinear model predictive control (NMPC) technique for EMS with an objective of achieving superior fuel economy. Initially, the framework of NMPC was developed and a transformed PSO was adopted for achieving desired optimisation. The approach uses a two-step optimisation process for achieving fast computation. The performance of the proposed approach was validated by performing simulation analysis based on the aggregated information collected from a driving cycle and a real bus. The efficacy of the proposed framework was evaluated by determining the rate of fuel consumption by SPHEV. It was observed that the energy consumption was significantly minimised by more than 10%. Wu et al. (2019) proposed application of deep learning algorithms for strengthening the performance of the EMS in electric vehicles. The study adopted a deep reinforcement learning algorithm for a series-parallel electric bus for assigning an appropriate power split of the electric bus. The deep RL based EMS was trained using different samples of driving cycles and the performance of the proposed approach was validated by comparing it with conventional RL methods. From results, it was observed that the deep RL-EMS showed significant enhancement in achieving optimised energy consumption compared to classical RL algorithms. Also, the Deep RL-EMS achieved efficient EMS strategies and explored the adaption of real time traffic data within vehicular EMS through enhanced algorithms. Peng et al. (2017) proposed a rule-based EMS for enhancing the performance of the parallel drivetrain, which is calibrated using dynamic programming (DP). The proposed approach applied DP for locating the optimal extensions for the ICE in parallel HEVs. The study introduces a recalibration technique for strengthening HEVs and the efficacy of the rule-based EMS was validated by evaluating DP algorithm.

3 Research methodology

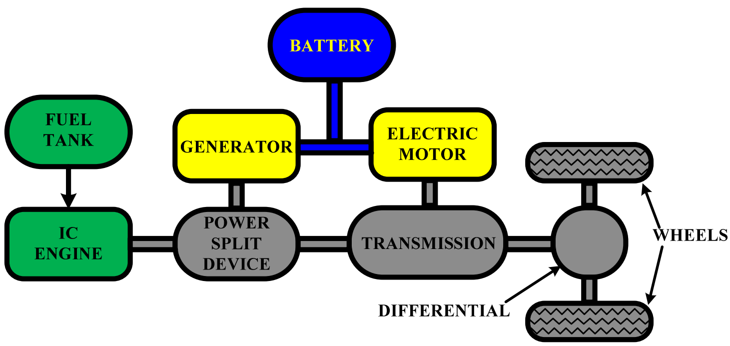
The preliminary objective of this research is to design and develop a hybrid electric vehicle model using reinforcement learning and fuzzy logic controllers for performance investigation and energy optimisation. The HEV model is developed using a series parallel drive train model which operates at near optimum efficiency to minimise the energy loss. The model is incorporated with the DRL algorithm for control and energy management of the HEV model. This study presents an enhanced EMS procedure based on deep reinforcement learning (DRL) algorithm. The DRL technique integrates Q learning and DRL algorithm to form an effective learning algorithm which can obtain action directly from the states, which is used to improve energy efficiency.

3.1 Design of hybrid electric vehicle model

A series parallel drivetrain based HEV is used for designing a HEV. The model employs a generator, an ICE), a device for storing the energy, coupling components for achieving mechanical coupling, a torque coupler and a traction motor. This model is flexible for operation and is feasible for optimising the torque-speed region. The series parallel drivetrain model is shown in Figure 1.

In the series parallel drive train model, the vehicle is driven by both ICE engine and motor. By combining the series and parallel designs, the engine can drive both the wheels directly (as in the parallel drivetrain), and can be disconnected effectively such that only one electrical device (either electric motor or ICE) is operated per cycle while the other is non-operative and continue to be in discharging state. The operating motor or ICE provides power (as in the series drivetrain) and the non-operative motor or ICE is responsible for charging the battery. However, there is a separate generator that charges the battery during regenerative braking. During braking, the motor behaves like a generator and the lost kinetic energy is restored in the battery. During driving, if the battery needs to be charged, ICE drives the generator to recharge the battery. When the vehicle stops, the battery can be still charged by the ICE via the generator. ICE supplies the steady state power and the motor is designed to achieve the stability by providing required initial acceleration during low speed conditions. Mechanical coupling is incorporated with torque and speed coupling. In the drivetrain used in this research, an electric generator is connected to the sun gear and ICE is connected to the planet carrier for speed coupling, whereas, the ring gear is connected to the wheels with the help of a fixed gear for torque coupling. The wheels are also connected to a traction motor through fixed gear for establishing coupling between the traction motor and output torque of the ring gear (Borthakur and Subramanian, 2018).

Figure 1 Series parallel drive train model (see online version for colours)



The maximum power generated by the ICE for a constant speed of v_{max} is presented as:

$$P_{eng(\max)} = \frac{1}{\eta_t}\left(Mgf_r \frac{1}{2}\rho C_d A v_{\max}^2\right) v_{\max} \tag{1}$$

where $P_{eng(\max)}$ is the maximum energy generated by the ICE, η_t represents transmission efficiency, M states the vehicle mass, f_r defines the coefficient of rolling resistance, C_d states the drag coefficient, $v_{\max}$ is the maximum voltage across ICE, ρ is air density whose value is 1.25 kg/m^3, and A defines the frontal area. P_m is the power rating of the electric motor, which is given as:

$$P_m = \frac{\gamma M}{2t_a \eta_t}(v_f^2 + v_b^2) \tag{2}$$

Where v_f is defined as the rated speed of the vehicle (km/h) and v_b states the speed of the vehicle with respect to the speed of the motor base and γ is defined as the rotational inertia factor, M is the vehicle mass and t_a is the acceleration time (Nandakumar and Subramanian, 2015). The rotational speed of the ICE (carrier), generator (sun gear) and ring gear is given as:

$$\omega_r = \frac{(1+k)}{k}\omega_{eng} - \frac{\omega_{eng}}{k} \tag{3}$$

where ω_r, ω_{gen}, ω_{eng} are the rotational speeds of ring gear, generator, and engine respectively, k is defined as the planetary gear ratio, stated as the ratio of the radius of the ring, R_r, to the radius of the sun, R_s.

$$v = \omega_W r_e (1-s) = \frac{\omega_r r_e (1-s)}{i_g} \tag{4}$$

where ω_W is defined as the wheel rotational speed, v is defined as the longitudinal speed of the vehicle and s is defined as the slip ratio. The torques which are shifted from the engine (T_{eng}) to the ring gear (T_r) and to the generator (T_{gen}) are defined as shown in the below equations.

$$T_r = \frac{k}{k+1} T_{eng} \tag{5}$$

$$T_{gen} = \frac{1}{k+1} T_{eng} \tag{6}$$

The shaft of the engine and the ring gear are connected through a final reduction gear with a gear ratio, i_g. Now, the overall wheel drive torque is defined using equation (7)

$$T_{wheels} = \frac{1}{i_g \eta_t}(T_m + T_r) = \frac{1}{i_g \eta_t}\left(T_m + \frac{k}{k+1} T_{eng}\right) \tag{7}$$

The specification of the series parallel drivetrain are tabulated in Table 1.

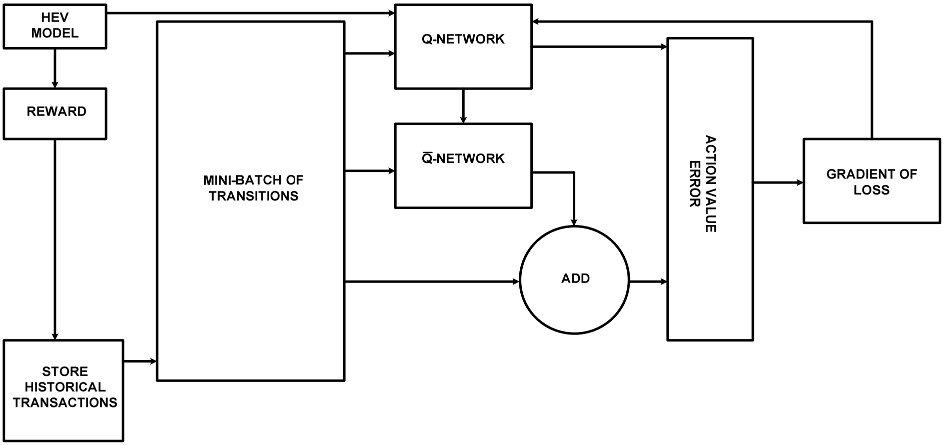
Table 1 Specifications of the series parallel drivetrain

Engine	Max.power (kW)	57
	Max.speed (rpm)	6000
Generator	Torque output (Nm)	80
	Max.speed (rpm)	8000
	Efficiency (%)	87
Traction motor	Torque output (Nm) at speed (rpm)	585 at 2500
	Max.power (kW)	123
	Max.speed (rpm)	12000
	Efficiency (%)	91
Batteries	Battery cells	120
	Initial capacity (Ah)	70
	Power (kW)	125
	Energy output (kWh)	88
Planetary gear ratio (k)		1.3
Final drive ratio		2.16

3.2 Control of series parallel drivetrain

There are different operation modes for controlling the operation of the drivetrain such as hybrid traction mode, regenerative braking etc. This study illustrates the application of a deep reinforcement learning algorithm for controlling the operation of the drivetrain and for effectively handling the EMSs. Figure 2 show the framework of DRL based EMS of an HEV.

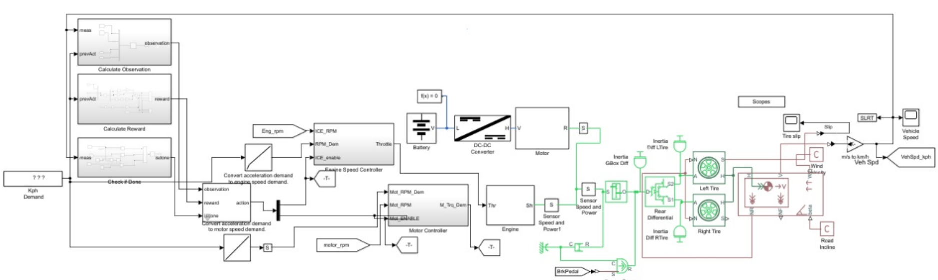
Figure 2 Framework of DRL based EMS of an HEV



In this study, the DRL-based EMS is proficient with an appropriate arrangement of system components which are dependent on input data with no prediction or predefined rules. The proposed DRL method is integrated with Q learning and DRL to develop an effective learning algorithm for enhancing energy efficiency. Reinforcement learning is used for analysing the system parameters and for generating the enable signal for generator, motor and ICE engine. RL takes input such as SOC of battery, vehicle speed, reference speed and IC engine RPM. In a series parallel drivetrain, the electric motor supplies the power to the vehicle and during high load conditions, the IC engine stabilises the system by supplying motor power to the vehicle. During braking, the IC engine powers the generator and the enable signal from the RL is given as shown in Figure 3. The reinforcement learning manager is used to create and train agents. These agents are generated using neural networks and the system is controlled by Q Learning. The reward observations are analysed from the simulink model.

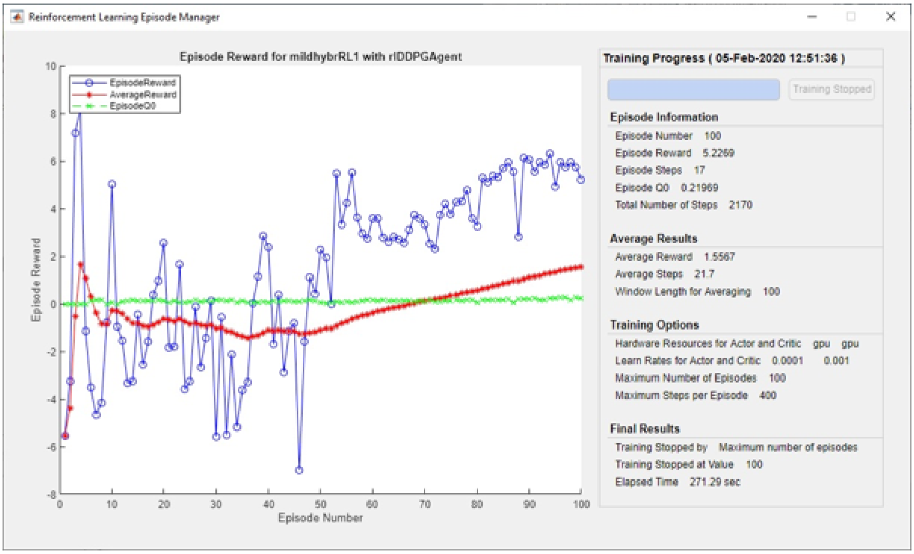
The simulink model of the HEV is controlled by DRL is presented in Figure 3.

Figure 3 Simulink model of HEV controlled by DRL (see online version for colours)



The reinforcement learning manager is given in Figure 4.

Figure 4 Reinforcement learning manager (see online version for colours)



The DRL-based EMS follows following steps:

- *System state*: The control mechanism of the vehicle is determined by its state. The required torque (T_{dem}) and the battery SOC are used for determining the state of the system which constitute a 2D state space i.e.,

  $$s(t) = (T_{dem}(t), SOC(t))^T.$$

- *Control action*: The prominent issue in the HEV-EMS is deciding the required torque-split ratio between battery and ICE. In this study, the ICE's output torque is considered as the control action, defined as $A(t) = T_e(t)$; t is defined as the time step index.

- *Immediate reward*: This is significant to the DRL since it prominently affects the functionalities of the DRL algorithm. The system components of the DRL will try to maximise the reward by considering the optimal action of every step. Hence the immediate reward is constituted based on the optimisation goal. The prominent intent of the HEV-EMS is to enhance the energy efficiency by minimising the fuel consumption without affecting the vehicle stability and state of battery. Based on this objective, the reciprocated value of the power utilisation by ICE at every time step is considered as the immediate reward. Additionally, a penalty value is included for penalising the steps when the SOC crosses the defined threshold value. Immediate reward is determined using the below mentioned equations (Hu et al., 2018):

$$r_{ss}^{a} = \begin{cases} \dfrac{1}{C_{ICE}} & C_{ICE} \neq 0 \cap 0.4 \leq SOC \leq 0.85 \\ \dfrac{1}{C_{ICE} + C} & C_{ICE} \neq 0 \cap SOC < 0.4 \text{ or } SOC > 0.85 \\ \dfrac{2}{Min_{C_{ICE}}} & C_{ICE} = 0 \cap 0.4 \leq SOC \\ -\dfrac{1}{C} & C_{ICE} = 0 \cap SOC < 0.4 \end{cases} \tag{8}$$

where the immediate award is defined by r_{ss}^{a}, given when the state of the vehicle shifts from s to s' by taking action a. C_{ICE} is defined as the instantaneous value of the fuel consumed by ICE and C is defined as the numerical penalty. $Min_{C_{ICE}}$ is defined as the minimum nonzero value of the fuel consumed by ICE.

- *DRL algorithm*: In this study, the DRL based EMS is defined in the algorithm given below. The two loops (outer loop and inner loop) control the EMS. The number of training states are controlled by the outer loop and the control of EMS within one training state is performed by the inner loop.

Algorithm 1 Deep Q-Learning with experience replay

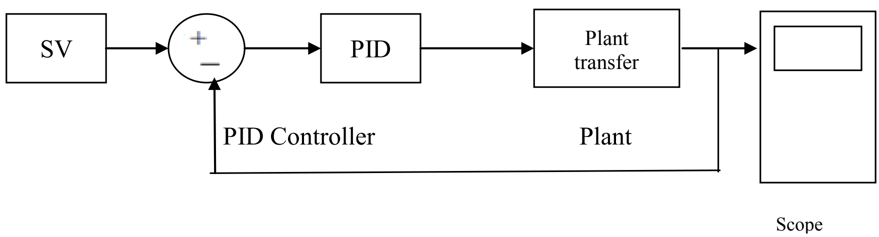
Initialization:
Step 1: replay memory K to capacity L
Step 2: action value component Q with random weights θ
Step 3**:** target action value component Q with random weights $\theta^{-} = \theta$
for episode = 1, N ***do***
Environment reset: s_o=($SOC_{Initial}$, T_o)
fort=1, T, **do**
Selecting a random action a_t for a probability of ε
else
Select a_t = maxQ(s_t,a;θ)
Parameter functioning:
Selecting action a_t and observing the reward r_t
Set:
s_{t+1} = (SOC_{t+1}, T_{t+1})
storing (s_t, a_t, r_t, s_{t+1}) in memory K
Sample random smaller group of (s_t, a_t, r_t, s_{t+1}) from K
if:
terminal s_{j+1}: set x_j=r_j
else
setsetx_j=r_j+ γmaxQ(s_{j+1},$a_{j+1;}\theta^{-}$)
performing a gradient descent step on $(x_j\text{-}Q(s_j,a_j;\theta))^2$
every C steps reset Q = Q
end for
end for

3.3 Fuzzy based PID controller

Fuzzy logic controllers with a self-tuning PID controller are used for parameter tuning of the HEV. Fuzzy-based PID controllers increase stability and provide efficient speed control and smooth torque.

- *PID controller*: The simulink model of the vehicle with PID controller is shown in Figure 5.

Figure 5 Simulink model of the plant with PID controller



The transfer function of the PID controller is defined as:

$$C(s) = K_P + \frac{K_1}{S} + K_d S = K_P \left(1 + \frac{1}{T_1 s} + T_d s\right) \tag{9}$$

where K_P K_i and K_d are defined as the proportional, integral and derivative gain of the controller, and T_i and T_d are the integral time and derivative time respectively.

- *Fuzzy logic control*

FLC is applied for the series parallel drivetrain based HEV, for maintaining constant speed irrespective of uncertainties such as variation in wind resistance and vehicle acceleration. The block diagram of the HEV with FLC and the basic structure of FLC is shown in Figures 6 and 7 respectively.

Figure 6 Block diagram of the HEV with FLC

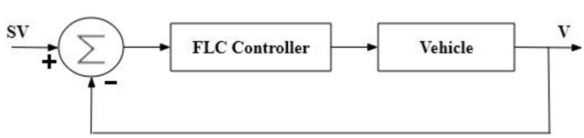
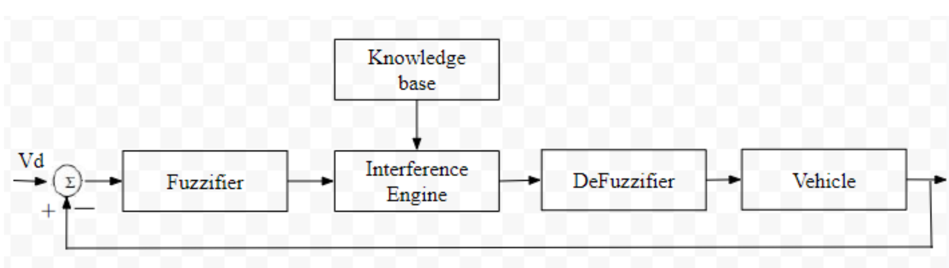


Figure 7 Basic structure of FLC



The design parameters of the fuzzy controller are selected based on the controller's input and output. Four main parameters such as base, inference engine, fuzzification and defuzzification are used for designing FLC.

The error (e) is selected as input to the FLC, given as (Yadav et al., 2011):

$$e(kT) = r - y \tag{10}$$

The change in error (ce) is given as:

$$ce(kT) = (e(kT) - e(kT - T)) / T \tag{11}$$

The output torque of ICE is considered as the output variable.

The basic fuzzy rules for FLC are tabulated in Table 2.

Table 2 Fuzzy rule base

ce	P	Z	N
P	PB	P	Z
Z	P	Z	N
N	Z	N	NB

where Z represents 'zero', P represents 'positive' and PB represents 'positive big'. The error difference is the change of error between one instance to another. If the error is positive then the speed of the vehicle is lesser than the set value and the controller should slightly increase the acceleration for increasing the speed. If the present error and error change are positive, then the speed of the vehicle is too slow and it shifts to decelerating mode and in such cases, the controller should increase the acceleration to maintain desired speed. These are known as fuzzy rules. For controlling the ICE using FLC, the RPM of the engine is compared to the IC engine demand which is further compared with IC enable signal from DRL. This generates the IC engine torque demand. Similarly, for controlling the motor, the RPM of the motor is compared with the motor engine demand and it is compared with motor enable signal from DRL. This generates the motor torque demand. The Fuzzy tined signals for ICE and motor are given in Figures 10 and 12 respectively.

4 Results and discussion

The fuzzy logic controller is used to tune the enable signal from the DRL. The fuzzy tuned signal is given in Figure 8.

The parameter tuning for both, engine and motor unit is performed using a fuzzy based PID controller. The simulink model of the fuzzy-based controller for controlling the speed of ICE and the fuzzy tuned signal for ICE is illustrated in Figures 9 and 10 respectively.

The simulation model of the engine control unit is shown in Figure 9.

Figure 8 Enable signal from DRL algorithm (see online version for colours)

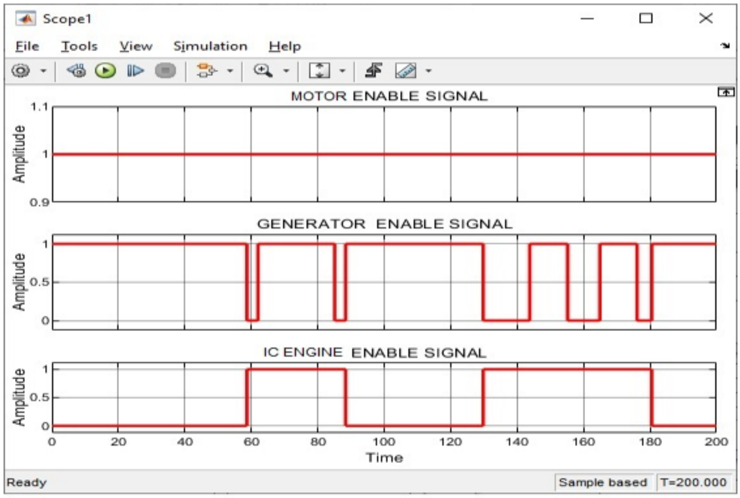
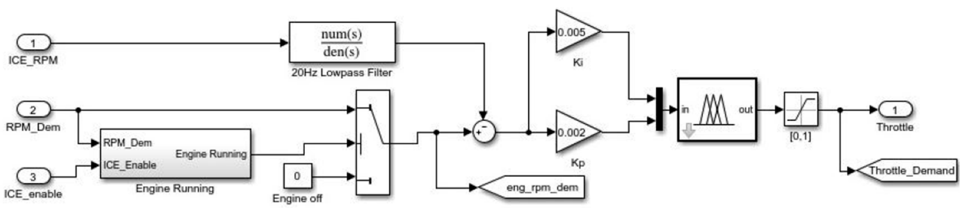
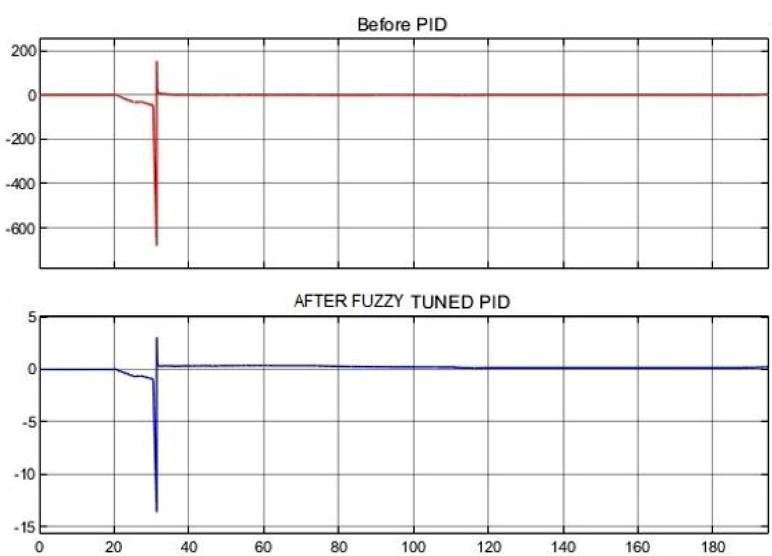


Figure 9 Engine control unit



The fuzzy tuned signal generated from engine control unit is given in Figure 10.

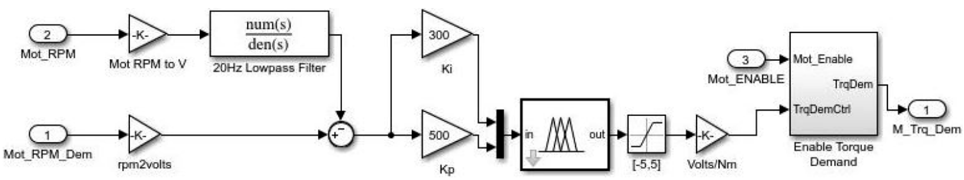
Figure 10 Before and after signals of fuzzy based PID controller for engine (see online version for colours)



In practical conditions, real-time systems deviate from the reference path due to driving uncertainties. This unexpected deviation affects the output of the engine and in such cases, the controller must be able to sustain the disturbance created in the engine. As observed from Figure 10, the fuzzy logic PD overshoot occurs and settling time of both FLC tuned PID and before PID are nearly the same. This shows that the response of the system is unaffected due to disturbances.

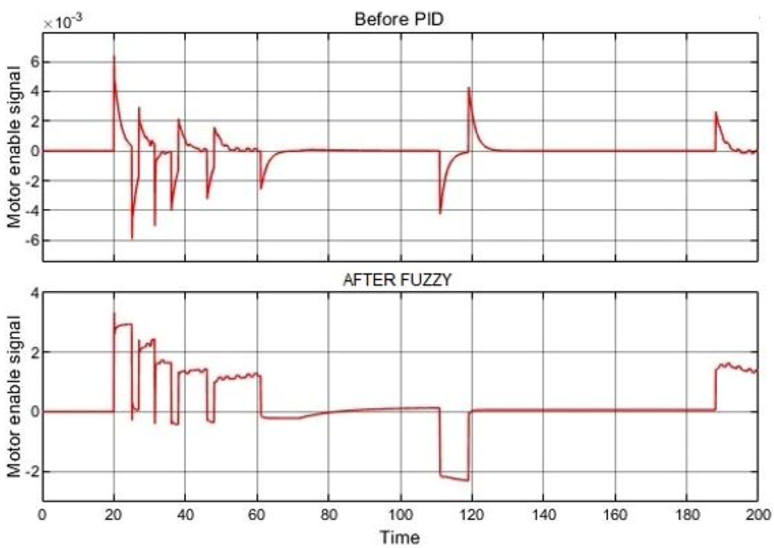
The simulink model of the fuzzy-based controller for controlling the speed of motor and the fuzzy tuned signal for motor is illustrated in Figures 11 and 12 respectively.

Figure 11 Motor control unit



The fuzzy tuned signal generated from engine control unit is given in Figure 12.

Figure 12 Before and after signals of fuzzy based PID controller for motor (see online version for colours)



The fuzzy tuned signal for generator is given in Figure 13.

Figures 12 and 13 show the response of the motor and generator respectively with and without FLC tuned signals. As observed from these figures, the response of the motor and generator improves with the tuning of the PID controller using FLC. The vehicle path is monitored and controlled by using Reinforcement learning methods. It is used for controlling the series parallel drivetrain and for minimising the energy consumption. The reference vehicle path and vehicle speed is shown in Figures 14 and 15 respectively.

Figure 13 Before and after signals of fuzzy based PID controller for generator (see online version for colours)

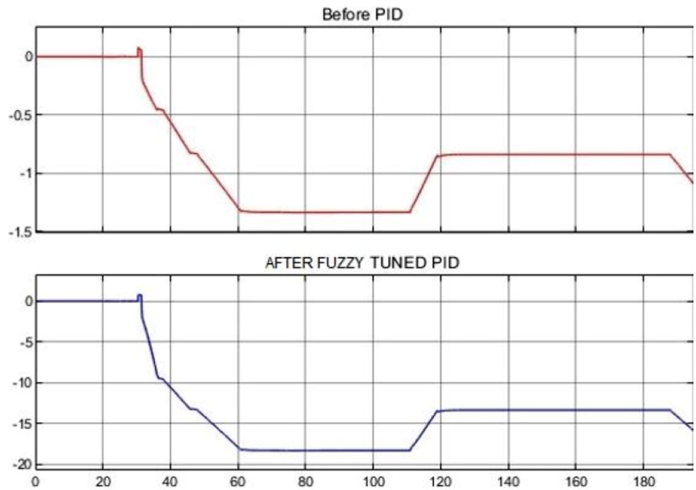


Figure 14 Reference vehicle path (see online version for colours)

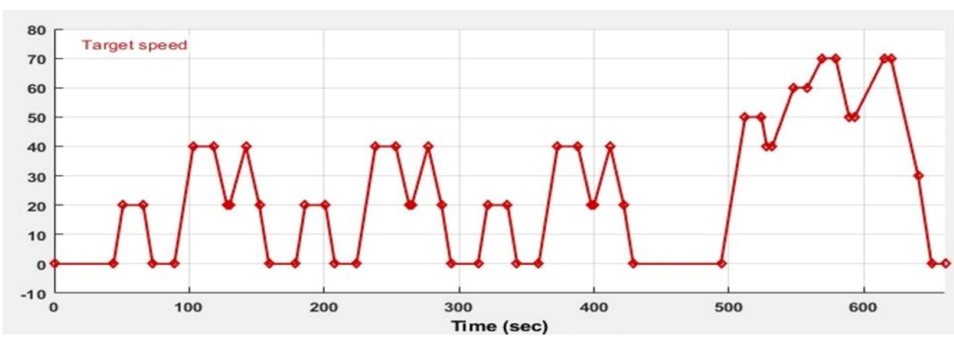
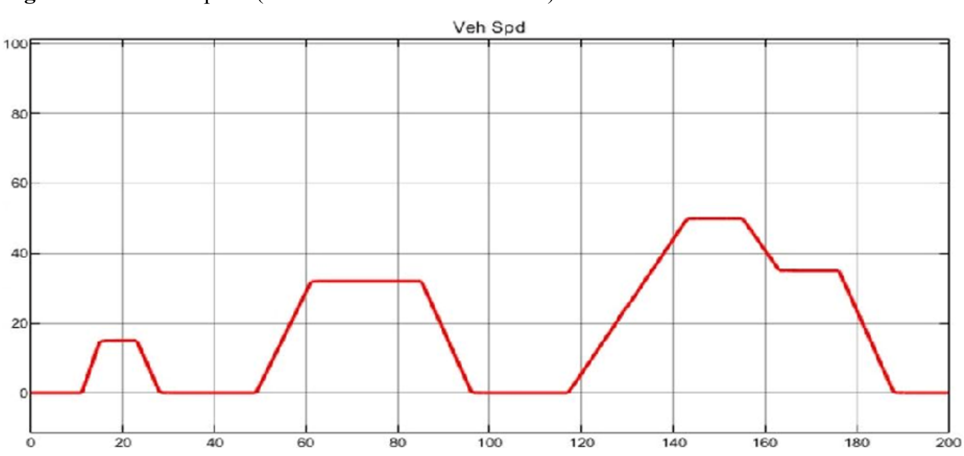


Figure 15 Vehicle speed (see online version for colours)



From the graph shown in Figures 14 and 15, it can be observed that the reinforcement learning method efficiently controls the speed of series parallel drivetrain and reduces the energy consumption of the drivetrain. The fuel economy for the HEV is shown in Figure 16.

Figure 16 Fuel economy

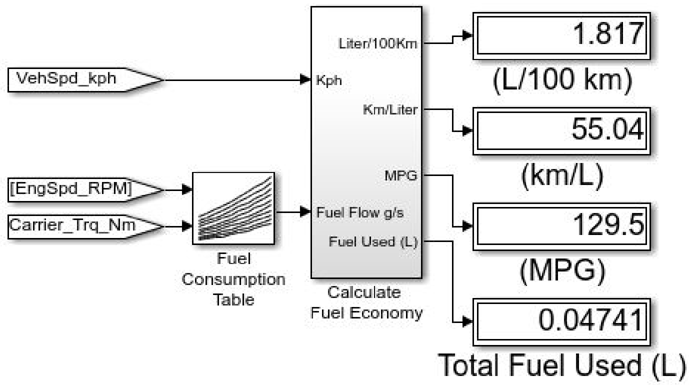


Figure 16 presents the fuel economy of the DRL based HEV model, the total fuel used was 0.04741 (L) for an average of 1.817 l per 100 km with a mileage of 55.04 km/L.

5 Conclusion

The preliminary objective of the research is to investigate the performance of an EMS in HEVs. Considering the influence of EMS in determining vehicle efficiency, an enhanced vehicular transition strategy based on a deep reinforcement learning-based framework was developed and applied for a series parallel drivetrain-HEV model. A DRL based deep Q-learning algorithm was developed for achieving energy optimisation in the HEV whose parameters were fine-tuned using a fuzzy based PID controller. The performance of the HEV model was validated from the simulation results and the prominent observations are as follows:

- The series parallel drivetrain offers the flexibility of selecting the mode of operation for the vehicle i.e., the vehicle can operate either with motor or ICE at once and the energy of the motor or ICE (which is shut down) will be used for charging the batteries. This significantly enhances the energy efficiency in HEVs.
- The vehicle path is monitored and controlled by the DRL algorithm, which effectively controls the series parallel drivetrain and minimises the energy consumption.
- Fuzzy based PID controls provide effective speed control for both motor and engine by fine tuning the motor and engine parameters.

From the simulation results, the effectiveness of the speed control mechanism can be observed. Following the vehicular reference path, the speed consistency was not much deferred as observed from Figure 15.

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